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Trust and Adoption of AI-Based Financial Advisory Services: An Examination of Investor Preferences

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Abstract

Keywords: Trust, Financial Advice, Human-advisor, Robo-advisor, Preferences, Decision-making.

This thesis aims to check if the nature of the financial advisor influences individuals' decision to follow or disregard the financial advice provided. The study collected data through an online survey, ensuring participant confidentiality and anonymity, and included participants from various countries and linguistic backgrounds. The dataset comprised 191 observations, combining qualitative and quantitative information, which were analyzed using STATA and Excel. The independent variables considered were the advisor's nature, risk profile, trust variables, and demographic characteristics. The study aimed to understand the effects of these variables on decision-making, with the dependent variable representing respondents' willingness to follow financial advice. The results revealed a different pattern when compared to previous studies, indicating that individuals might be indifference between human and robot advisors. Risk profiles influenced the inclination to follow advice, while personal characteristics had a minimal impact. Participants generally exhibited higher trust in human advisors, although robo-advisors were perceived as more trustworthy in terms of conflict-free services. Higher trust and education levels increased the likelihood of following advice, while individuals with higher risk profiles were more likely to disregard the advice. The nature of the advisor did not significantly influence decision-making, emphasizing the importance of trust in shaping individuals' choices. The study contributes to the understanding of human-robot interaction and provides insights for financial institutions and policymakers to enhance advisory services. Future research could explore additional factors influencing decision-making and tailor advice based on individual suitability to improve outcomes in an evolving digital landscape.

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1. Introduction

The constant and rapid development of technology has brought transformative changes in various aspects of our world. From automating everyday tasks to creating new tools, technology has reshaped societal demands and relationships. In recent times, the public release of AI-based tools, such as Chat-GPT, YOLO, Wealthfront and Betterment among others, have further intensified the spotlight on the intersection of humans and artificial intelligence (AI) in different domains, including financial advisory services. This development has brought new insights and perspectives to the discourse surrounding AI-based financial advice and its implications.

Robo-advisory services have been the subject of extensive research, exploring their strengths, weaknesses, opportunities, and threats (Jung, Glaser & Köpplin, 2019). However, with the emergence of AI tools and their increasing accessibility to the public, it becomes crucial to examine how people's attitudes towards AI-based financial advice have evolved. The public release of AI tools has shed new light on the possibilities and limitations of robot-advisors, thereby possibly influencing individuals' perceptions and preferences.

Understanding the evolving perceptions and preferences regarding robo-advisors is essential in comprehending the impact of technology on the financial advisory field. Even though previous studies suggest a greater trust in human financial advisors compared to algorithmic or robotic counterparts (Zang, Pentina & Fan, 2021), as technology becomes more prevalent, it is necessary to investigate whether people's attitudes towards AI-based financial advice have shifted, and if trust continues to play a significant role in their decision-making processes. Exploring these dynamics is crucial for both researchers and practitioners in the financial industry.

Therefore, the primary objective of this study is to delve into the intricate dynamics between humans and AI in the context of financial advisory services, considering recent rapid developments in AI technology. By exploring the evolving perceptions and preferences regarding robot-advisors, this study aims to contribute to the understanding of how technological advancements shape individuals' attitudes and decision-making processes.

The research questions that guide this study are as follows:

> *Research Question 1: Does the nature of the financial provider (human or AI-based) influence individuals' decision to follow or disregard the advice provided?*
>
> *Research Question 2: Is lack of trust a significant obstacle to the adoption of AI-based financial advisory services? If so, is there a specific aspect of trust that is more prominent?*

To address these research questions, the literature review provides a comprehensive overview of existing studies examining individuals' perceptions and preferences in the financial advisory field, human-AI interactions, and trust within the financial context. By relating these topics to the research questions, the section contributes to the understanding of the role of trust in the adoption of AI-based financial advisory services in the current context.

The methodology employed in this study provides insights into individuals' preferences and degree of trust. An online survey that elicited individuals 'risk attitudes to provide tailored financial advice, was designed and distributed in Europe and Brazil to capture a diverse range of perspectives. The survey instrument also includes Likert Scale questions to measure trust and an open-ended question to capture participants' nuanced reasons for non-adoption of the AI-based financial advice. The dataset consists of both qualitative and quantitative information, which was analyzed separately using appropriate statistical techniques. The analysis includes descriptive statistics, regression analysis, and qualitative analysis of open-ended survey responses.

Findings indicate that the nature of the financial provider does not influence individuals' decisions, but risk profiles have an impact on their inclination to follow financial advice. Personal characteristics such as gender and education did not show a significant impact on the inclination to follow advice based on the nature of the advisor. In terms of trust, participants exhibited higher overall trust in human advisors, while robo-advisors were perceived as more trustworthy specifically in terms of providing conflict-free services. Furthermore, participants who intended to follow the advice, regardless of the advisor, had higher trust scores. This suggests that trust plays a crucial role in individuals' decision to follow financial advice, regardless of the source.

Further analysis through OLS regression confirmed the trends observed in the descriptive statistics and provided more detailed insights. Higher levels of trust and education were associated with an increased likelihood of following the advice. On the other hand, individuals with higher risk profiles were more inclined to disregard the financial advice provided. The model also found evidence indicating that trust in the advice itself had a more substantial impact on the decision to accept or reject the advice than the specific nature of the advisor.

The open-ended question in the survey allowed for a qualitative analysis of the reasons why respondents decided not to follow the advice provided. Most concerns revolved around intrinsic characteristics of the financial advice and the determination of participants' risk profiles, highlighting limitations in the survey and the study. Concerns about conflicts of interest were only mentioned in relation to advice from human advisors, while a third of respondents who received advice from robo-advisors cited the nature of the advisor as the primary reason for disregarding it.

Overall, these findings contribute to our understanding of the role of trust in the adoption of AI-based financial advisory services. They highlight the importance of trust in the advice itself, regardless of whether it is provided by a human or a robot advisor. The results also underscore the need for financial institutions and policymakers to address concerns related to risk perception, conflicts of interest, and the robotic nature of AI-based advisors to build and maintain trust with clients.

Furthermore, the findings contribute to the growing body of literature on human-robot interaction and provide insights into individuals' preferences and trust dynamics in the evolving landscape of financial advice. Through a comprehensive analysis of quantitative and qualitative data, this study seeks to contribute to our understanding of financial advice and trust, with the goal of informing the development of tailored and effective financial advisory services in an increasingly digital world.

This study is composed of an extensive review of the existing literature, a comprehensive description of the survey and research methods employed to address the research questions and test the hypotheses, a thorough analysis of the collected data and presentation of the results, a detailed discussion of the findings in relation to the research objectives along with an examination of the study's limitations, and a conclusion summarizing the key insights and implications.

2. Literature Review

The integration of artificial intelligence (AI) in financial advisory services has brought about significant changes in the financial landscape. Gokul (2018) highlights that AI has rapidly transformed various aspects of financial operations and regulations, including risk management of projects, fraud detection in the banking sector, trading security, portfolio management, and the analysis of complex market graphs to predict future rates of return. With the increasing prevalence of AI-based financial advisors, there is a growing need to examine the role of trust in the adoption of these AI-driven solutions. This section aims to delve into existing knowledge on individuals' perceptions and preferences in the financial advisory field regarding human or AI advisors, as well as the role of trust within the financial context. In addition to drawing upon academic research, this exploration will be enriched by the author's personal past experience of working in the financial markets, providing valuable insights into the evolving landscape, and contributing to a multifaceted understanding of the role of trust in the adoption of AI-based financial advisory services in the current context.

To gain insights into individuals' preferences regarding human or AI advisors, it is essential to establish a conceptual framework for each of these entities. A Certified Financial Planner (CFP®) can be identified as a financial advisor who possesses the globally recognized CFP® certification, conferred by the Financial Planning Standards Board (FPSB). This certification attests to their expertise in financial planning, taxes, insurance, estate planning, and retirement saving. On the other hand, robo-advisors can be defined as comprehensive automated online advisory platforms that assist investors in managing their wealth by providing recommendations for portfolio allocations based on predefined algorithms (Bhatia et al., 2021).

The role of a Certified Financial Planner is grounded in their specialized knowledge and skills acquired through the CFP® certification and fulfillment of necessary requirements over time. This certification serves as a benchmark for ensuring the competence of financial advisors in various domains of financial planning, reflecting a comprehensive understanding of the intricacies involved in managing clients' financial affairs. In contrast, robo-advisors leverage AI-driven algorithms to provide automated and algorithm-based financial advice, relying on predetermined risk analyses, mathematical models, meta-analyses, and historical data to generate portfolio recommendations for investors.

Robo-advisory services provide an alternative approach to traditional financial advisory. Robo-advisory has adapted and digitalized traditional phases and fulfils basic functionalities of financial advice in wealth management (Cocca 2016). The key benefits of the investment process of robo-advisors are the personalized approach of using questionnaires, the suggestion of a portfolio based on academic evidence, the simple use, automated rebalancing as well as continuous monitoring of investments (Jung, Glaser & Köpplin, 2019). However, like other self-service technologies, robo-advising may cause anxiety and stress for consumers (Zang, Pentina & Fan, 2021).

Although artificial intelligence and algorithms have its efficiency recognized and even adopted by high-profile financial companies, such as BlackRock (Tokic, 2018), is still common for people to prefer the advice of human financial advisors. Both Longoni *et al.* (2019) and Luo *et al.*(2019) conclude in their studies that consumers still prefer human interactions in industries characterized by high consumer involvement, such as health care and financial services. Zang, Pentina & Fan (2021) provide evidence suggesting that people have a greater level of trust in human financial advisors with elevated level of expertise compared to algorithms/robot financial advisors.

In their study, Bhatia et al. (2021) identified several factors that significantly influence individual investors' perceptions of robo-advisors in India, including cost-effectiveness, trust, data security, behavioral biases, and investor sentiments. The participants perceived robo-advisors only as a supplementary service, strongly believing that human intervention is necessary to gauge the emotions of investors. Cocoa (2016) conducted a study with private banking clients in Austria, Germany, and Switzerland and found evidence that a hybrid advisory model offered by established wealth managers would be the most promising advisory model for the main customer segments in wealth management.

The recent public release of new AI tools has brought additional attention to the theme of AI-based financial advice and might have influenced individuals' perceptions. The availability of AI-based financial advisory services has expanded individuals' exposure to AI in the financial realm.

Millennials, who were born between the mid-1990s and early 2000s, are the primary target group of robo-advisors, as they constitute an investor group attracted by using technology in counterpoint to older investors who are discouraged by it (Sironi, 2016).

While specific studies focusing on the impact of new AI releases on investors' behavior are limited, it is plausible that the introduction of these tools might have altered individuals' perceptions of robo-advisors and influenced their trust in AI-based financial advice. Fulk, Watkins & Kruger (2018) conducted a study and found that consumers in the United States who used a traditional financial planner were typically older had higher levels of net worth, and a larger portion of their total net worth came from inheritance. In contrast, consumers who preferred to use the services provided by robo-advisors generally had lower income, lower net worth, received little to no inheritance, and exhibited less impulsive financial behavior.

Recent studies have found evidence that personal characteristics, such as gender, age, education level, and income level, might play a significant role in participants' inclination to follow financial advice provided by AI-based advisors. Gonzalez-Igual, Santamaria & Vieites (2021) provided evidence that female investors view themselves as more driven by rational analysis and are more risk-averse, while younger investors are more influenced by cognitive and emotional biases.

Another factor that might be correlated with investors' preferences regarding whether to follow advice from AI-based advisors is the investor's risk profile. Kim, Cotwright, & Chatterjee (2019) found that robo-advisor users were younger investors with high risk tolerance, who self-assessed their financial knowledge comparatively higher than their actual knowledge and were independent decision-makers.

Taking into consideration the existing findings and the significant technological advancements that have occurred over the last 24 months, this study aims to answer its first research question and test the following hypotheses:

> *Research Question 1: Does the nature of the financial provider (human or AI-based) influence individuals' decision to follow or disregard the advice provided?*
>
> *H1: Overall, people are more inclined to follow the advice from human financial advisors than from AI-based financial advisors.*
>
> *H2: Risk profiles and personal characteristic play a role in participants' inclination to follow financial advice provided by AI-based advisors.*

To examine the role of trust in the adoption of human or AI financial advisory services, it is essential to develop a comprehensive understanding of the concept of trust and how its perceived by individuals. Trust has been a subject of extensive research across diverse disciplines, including sociology, psychology, philosophy, political sciences, business, and economics, among others. This interdisciplinary approach reflects the recognition of trust as a fundamental concept that holds multifaceted meanings and can be interpreted through various lenses, influenced by disciplinary perspectives and cultural contexts. Each field of study offers a unique and intricate definition of trust, contributing to the complexity of its conceptualization.

While consensus regarding the precise definition and scope of trust remains elusive, scholars have endeavored to develop a universal framework that encompasses trust across diverse domains. Aiming to transcend disciplinary boundaries and capture the fundamental elements of trust that are applicable across various fields of study, Robbins (2016), for instance, proposed a multifaceted model that incorporates cognitive and structural dimensions of trust. According to this model, trust comprises a belief (how) about the trustworthiness of another person (who) in relation to a specific matter (what), emerging in situations of unknown outcomes.

Within the business context, Ennew & Sekhon (2007) state that trust is commonly understood as an individual's willingness to accept vulnerability based on positive expectations about the intentions or behavior of another person, particularly in situations characterized by interdependence and risk. In the realm of financial markets, the decision-making process of hiring a financial advisor and following their advice aligns with this description of risk and interdependence.

The financial market environment is complex, with a multitude of products, which have subtle differences, and require expert knowledge to be fully comprehended. As a result, clients find themselves in a challenging scenario and vulnerable position when making decisions about financial investments and thus, decide to seek the assistance of financial advisors. By hiring a financial advisor and implementing their recommendations, clients place their trust in the professional's expertise and expect positive outcomes.

The willingness to be vulnerable might arise from factors such as a cost-benefit analysis, an individual's predisposition to trust, a deep knowledge and understanding of exchange partners, or a faith in social systems and institutions (Ennew & Sekhon, 2007). When considering the decision to engage a financial advisor, clients often conduct a cost-benefit analysis, evaluating the potential advantages and disadvantages of seeking professional advice. Additionally, an individual's predisposition to trust, might be shaped by their past experiences and personal characteristics, influencing their willingness to rely on the financial advisory. Furthermore, clients might use their knowledge and understanding of the financial market and its participants to determine their level of trust in a financial advisor.

Understanding the dynamics of trust within the financial context is not only essential for comprehending clients' decision-making processes but also for promoting the success of businesses in the industry. Fergeson (2003) highlights that an American Bankers Association study revealed that more than half of bank customers prioritize establishing a relationship of trust with their financial institution over obtaining the best value for their money. This finding underscores the significance of trust, as it surpasses price considerations in the eyes of customers. Furthermore, Devlin et al. (2015) conducted a retrospective analysis of trust levels in the financial markets, revealing that fluctuations in trust were primarily driven by the reputations of market players rather than the financial crisis periods. Additionally, the financial sector as a whole was found to be trusted more than other public and private organizations used as comparator institutions, such as The National Health Service (NHS) and The British Broadcasting Corporation (BBC).

Differences in trust levels within various segments of the financial industry indicate the potential for divergent levels of trust between human-provided and AI-based financial advisory services. Tyler & Stanley (2007) identified asymmetrical perceptions and operationalizations of trust across dyads and segments, with smaller companies exhibiting greater trust compared to larger corporates. Bankers employed calculative and operational trust, expressing cynicism toward the trustworthiness of their counterparts, and swiftly eliminating clients who they believed did not provide complete disclosure of relevant information. Similarly, Monti et al. (2014) observed that trust formation in financial advisory contexts relies heavily on a heuristic centered on the advisor's communication style. Investors' decisions regarding portfolio delegation were influenced more by perceptions of the investor-advisor relationship than by the risk and return characteristics of the investment options. Analogously, these findings suggest the potential for varying trust dynamics between distinct types of financial advisors, both human and AI-based.

Trust is undoubtable a crucial factor in the adoption of AI-based financial advisory services, to better explore the role it plays in our study, the following research question and hypothesis will be tested:

Research Question 2: Is lack of trust a significant obstacle to the adoption of AI-based financial advisory services? If so, is there a specific aspect of trust that is more prominent?

H3: Lack of trust is a significant obstacle for people to use AI-based financial advisory services.

3. Methodology

This section presents the comprehensive methodology employed in the present study to investigate the role of trust in individuals' decision-making process when choosing whether or not to follow the financial advice of a human professional (Certified Financial Planner - CFP) or a robot (AI-based).

3.1 Research Design

To gain a comprehensive understanding of trust in the financial advice decision-making, an online survey[1] was chosen as the research methodology. This approach enabled the collection and analysis of both quantitative and qualitative data in a streamlined manner. The survey comprised a questionnaire that can be categorized into four distinct blocks for ease of explanation: i) Lottery Questions, ii) Financial Advice Presentation and Decision Question, iii) Trust Assessment Questions, and iv) Background Questions.

It is important to emphasize that within the survey's introduction, all participants were explicitly informed that the portfolio recommendations and risk analyses presented in the study were derived

[1] The full survey is available in Appendix A - Survey.

from actual financial planning rules. Ethical considerations were given utmost importance throughout the study. Informed consent was obtained from all participants, and their confidentiality and anonymity were ensured. Participants were informed about the purpose of the study, the voluntary nature of their participation, and the expected time necessary to conclude the survey (approximately 5-10 minutes). It was explicitly stated that the survey was part of a master thesis of the Behavioural Economics course at Erasmus University of Rotterdam. The researcher's contact information was provided for any further questions or concerns.

The survey was made available in two languages, English and Portuguese, to accommodate participants from different linguistic backgrounds and countries. Once the survey was completed, all participants received a message thanking them for their participation, and the researcher's contact information was displayed again for any additional queries or feedback.

As the survey was conducted online, participants had the freedom to stop answering questions and leave the website at any point without facing any consequences. The age requirement for participation was set at 18 years or older to ensure legal consent and appropriate understanding of the study. By incorporating these ethical considerations and providing clear information to participants, the study aimed to maintain a high standard of research integrity and participant well-being.

Subsequent to the introduction, the lottery block was presented, serving as means to determine participants' risk profiles. Based on respondent’s answers, a financial advice was provided, randomly attributed to either a human professional (CFP®) or a robot (AI-based) then, participants were asked to indicate whether they would follow the advice given or not. Subsequently, a Likert-scale questionnaire was presented to assess participants' agreement with four trust-related statements, and an open-ended question was included, allowing participants to state their main reason for not following the advice, if applicable.

An organizational chart with the detailed and complete survey flow is available in Appendix A – Survey Logic Flow.

3.1.1 Risk Profile Elicitation

The lottery questions in this study served to capture participants' risk preferences and establish their risk profiles in accordance with the principles of Expected Utility Theory. The structure and ordering of the lottery questions were carefully crafted to ensure systematic assessment of the risk degree, assuming that subjects have complete and transitive preferences. Drawing inspiration from the study by Donkers, Melenberg, & Van Soest (2001), the design of the lottery questions adhered to the rule that lotteries with higher risk also offered higher expected values. The details of each lottery are available on the Appendix A – Lottery Question Design of this study.

It is important to note that the lottery questions employed in this study represent an alternative method for determining participants' risk profiles. In traditional settings, financial advisors often use suitability forms or long questionnaires to assess individuals' risk tolerance. However, given the nature of this study, it was not feasible to utilize the common methods. Hence, the lottery questions were devised as a practical and effective approach to gather information about participants' risk profiles within the constraints of an online survey.

The set of lottery questions comprised five distinct lotteries, always presented in pairs. Each of the lotteries represented one of the five commonly known investor risk profiles (1- conservative, 2- moderately conservative, 3- moderate, 4- moderately aggressive and 5 – aggressive). The order of the questions was strategically arranged to facilitate a comprehensive understanding of participants' risk profiles in an efficient and logical manner, for more details please refer to Appendix A – Survey Logic Flow.

All lottery questions are presented below:

Question 1:

You received a voucher of €100.00 to play one of the two lotteries described below. Which of the following options would you choose?

A. *Play the lottery in which you have 75% of chance of receiving €70.00 and 25% of chance of receiving €130.00.*
B. *Play the lottery in which you have 50% of chance of receiving €40.00 and 50% of chance of receiving €150.00.*

Question 2.0:

You received a voucher of €100.00 to play one of the two lotteries described below. Which of the following options would you choose?

A. *Receive €75.00 for sure, and do not play a lottery.*
B. *Play the lottery in which you have 75% of chance of receiving €70.00 and 25% of chance of receiving €130.00.*

Question 2.1:

You received a voucher of €100.00 to play one of the two lotteries described below. Which of the following options would you choose?

A. *Play the lottery in which you have 50% of chance of receiving €40.00 and 50% of chance of receiving €150.00.*

B. *Play the lottery in which you have 80% of chance of receiving €2.00 and 20% of chance of receiving €500.00.*

Question 3:

You received a voucher of €100.00 to play one of the two lotteries described below. Which of the following options would you choose?

A. *Play the lottery in which you have 70% of chance of receiving €35.00 and 30% of chance of receiving €250.00.*
B. *Play the lottery in which you have 80% of chance of receiving €2.00 and 20% of chance of receiving €500.00.*

In the first lottery question, participants were presented with a choice between a lottery representing the middle profiles: moderately conservative (2) and moderate (3). This initial choice served as a pivotal point for subsequent questions, as it provided an indication of participants' risk preferences.

If a participant opted for the less risky option (moderately conservative) in the first question, a second question followed. This second question offered participants a choice between the moderately conservative profile (2) and the conservative profile (1). By answering this question, the participant was categorized as conservative (risk profile 1) or as moderately conservative (risk profile 2).

Conversely, if a participant chose the riskier option (moderate) in the first question, a different second question was presented. This alternative second question consisted of a choice between the moderate profile (3) and the aggressive profile (5). By selecting the moderate lottery again, the participant's risk profile was determined as moderate (3). Conversely, if the riskier alternative was chosen (aggressive), another question was presented with two lotteries representing the moderately aggressive profile (4) and the aggressive profile (5), this last answer determined whether the participant was moderately aggressive (risk profile 4) or aggressive (risk profile 5).

Based on the staircase procedure used by Falk et al. (2018), every subsequent question followed a similar structure, and was built upon participants' previous choices in a progressive manner. Each subsequent question presented the lottery option chosen earlier alongside a new option that could have a lower or higher level of risk. If participants selected the less risky option in the initial question, the subsequent question offered a choice between the same level of risk and a lower level of risk. Conversely, if participants opted for the riskier lottery in the initial question, the subsequent scenario presented the chosen lottery alongside an even riskier option. The third question was only presented to participants who consistently selected the riskier lotteries, and in this case, the options included the riskiest lottery chosen in the second question and an intermediary one, with a little less risk.

By incorporating this systematic approach, all five risk profiles were effectively determined based on participants' choices in the series of lottery questions. The gradual increment/decrement of risk in the lotteries, coupled with the descriptive properties of eliciting preferences, facilitating a comprehensive understanding of participants' risk profiles in a structured and efficient manner, analogous to the elicitation method used by Abdellaoui et al. (2008) in their experiment.

The lottery questions served as a practical and reliable means of capturing participants' risk preferences within the online survey context. However, it is essential to acknowledge that this alternative method might not replicate the precise results obtained from traditional suitability forms. Additionally, the accuracy of participants’ risk profile determination relies on the assumption that they did not make any mistakes when choosing their answers.

The absence of a face-to-face interaction and the limitations associated with online surveys necessitated the development of a pragmatic approach to assess risk profiles. Nonetheless, the systematic structure of the lottery questions ensured the reliability and validity of the risk profiles derived from participants' responses, enhancing the robustness of the study's findings.

3.1.2 Financial Advice Presentation and Decision Question

Following the lottery questions, participants were presented with a hypothetical scenario involving a financial advice recommendation. This scenario aimed to assess participants' decision-making regarding whether they would follow the advice provided by either Augustus, an AI-based financial advisory (robot), or Augustus, a Certified Financial Planner (CFP®).

Participants were asked to imagine having €1,000.00 available for investment and then received a message from Augustus, either the AI version or the human one. The nature of the financial advisor was randomly assigned to each participant to ensure unbiased distribution, ensuring an equitable comparison between the two sources of advice.

The financial advice presented by Augustus, both the AI-based financial advisor and the CFP®, followed the same format and were derived from actual financial planning rules. The recommendation considered the participant's previously determined risk profile, as established through the lottery questions.

For example, participants might have received the following message from Augustus, either the AI-based financial advisor or the Certified Financial Planner (CFP®):

> *"Hi. My name is Augustus, I'm an AI-based financial advisory (robot) [Certified Financial Planner (CFP®)], and I would like to recommend a portfolio investment for you. I have drawn your risk profile based on the answers you provided previously. I believe you should*

invest 85% of this amount (€850.00) in an asset without risk. By applying this investment strategy, you can expect to have €892.50 (5% return rate) after 12 months. The remaining 15% (€150.00) should be invested in a risky asset, which has an equal probability of reaching €225.00 (+50% return rate) or decreasing to €75.00 (-50% return rate) after 12 months."

The portfolio recommendations[2] and risk analyses were in accordance with the financial planning guidance for Certified Financial Planner (CFP®) holders. It is noteworthy that the author of this study has been a CFP® practitioner since January 2018 and possesses extensive experience in the Brazilian financial market, with a professional tenure of 8 years. This practical background and professional expertise enabled the author to apply their comprehensive knowledge and insights to ensure that the financial advice provided in this study was informed by both theoretical principles and practical industry experience.

Based on the language selected (English or Portuguese), certain adjustments were made to the scenarios presented in the portfolio recommendation to ensure their relevance and applicability to participants' respective contexts. These adjustments included considerations such as the currency, the interest rate for the risk-free asset and the income ranges.

In the English version, the return rate for the risk-free asset (5% annually) was based on the American Treasury Bill, reflecting the prevailing rates in the corresponding financial market. On the other hand, in the Portuguese version, the return rate for the risk-free asset (13% annually) was based on the SELIC rate, which is the benchmark interest rate in Brazil. These adjustments aimed

[2] A table with the portfolio's recommendations for each one of the 5 risk profiles is available in the Appendix A – Financial Advice Design.

to align the questionnaire with the financial norms and practices specific to each language group, ensuring that the scenarios accurately represented the reality of the participants.

By tailoring the scenarios to the participants' language selection, the study sought to enhance the participants' engagement and comprehension of the financial advice presented. This approach aimed to provide a more realistic and relatable decision-making context, ultimately contributing to the validity and applicability of the research findings within the respective language groups.

After presenting the financial advice, participants were asked the following question:

> *"Would you follow the financial advice provided by Augustus, an AI-based financial advisory (robot)?"*

or

> *"Would you follow the financial advice provided by Augustus, a Certified Financial Planner (CFP®)?"*

This question aimed to gauge participants' inclination to follow the financial advice provided, considering the information presented and their individual risk profiles.

Participants were explicitly instructed to provide a binary response (Yes/No) to this question, independent of their responses to the preceding questions. The purpose of this question was to capture participants' immediate inclination to accept or reject the financial advice received. The binary response format facilitated a straightforward assessment of participants' willingness to follow the advice given, allowing for a direct comparison between the AI-based advisor and the human advisor. This format further facilitated the analysis of participants' preferences and trust in each advisory approach.

3.1.3 Trust Assessment Questions.

Following the "financial advice presentation and decision question" block, participants were invited to express their level of agreement with four trust-related statements using a 1-5 Likert scale, in which the scale ranged from 1 (strongly disagree) to 5 (strongly agree). These statements aimed to capture participants' perceptions of trust towards the financial advice provided by Augustus, whether in the form of the AI-based advisor or the CFP®. It is worth noting that all statements were specifically formulated to ensure that by strongly agreeing with it the participant demonstrates a higher level of trust. The four statements were as follows:

1. *"Overall, I feel I can trust the financial advice provided."*
2. *"I believe that this financial service provider has my best interests in mind."*
3. *"I trust the risk management strategies of the financial advice provided."*
4. *"I am confident of the accuracy of the financial information provided by this service."*

Upon completion of the Likert scale questions, participants were presented with an open-ended question intended to explore the primary reasons behind their decision to not follow the financial advice provided. The open-ended question read as follows:

> *"If you chose not to follow this financial advice, could you state one main reason for your choice? Otherwise, please skip this question."*

Participants were encouraged to provide a brief explanation of their decision, highlighting the factors or considerations that influenced their decision in not following the advice received. The inclusion of the open-ended question aimed to test if by giving participants an opportunity to state any reason to justify their decision, trust would be representative or not. This question also allowed for a more nuanced understanding of participants' decision-making processes and provided valuable qualitative insights into their perceptions concerning the offered financial advice.

The responses to the open-ended question aimed to ascertain whether participants would attribute their decision to not follow the AI-based portfolio recommendations primarily to a lack of trust, while potentially indicating other diverse reasons for disregarding the recommendations provided by the CFP® or AI advisor. This additional qualitative dimension complemented the quantitative assessment of trust and further enriched the analysis of participants' decision-making behaviours in the context of financial advice acceptance.

3.1.4 Background Questions.

In the survey's final block, participants were asked to provide some background information by answering a series of questions. These questions aimed to gather data on respondents' characteristics that might influence their responses and decision-making process. The background questions included the following:

- *Age Range: Participants were asked to select their age range from a provided list of options.*
- *Gender: Participants were asked to indicate their gender identity from the provided options.*
- *Country of Residence: Participants were asked to specify their country of residence using an open-ended question.*
- *Income Range: Participants were asked to select their approximate annual income from a provided list of options.*
- *Level of Education: Participants were asked to indicate the highest level of education they have completed from a provided list of options.*
- *Financial Education/Knowledge: Participants were asked to rate their perceived level of financial education/knowledge on a scale ranging from "No knowledge at all" to "Professional knowledge."*

These background questions aimed to capture demographic and contextual information about the participants, enabling the analysis of how respondents' characteristics might influence their responses. For example, by examining the data, it would be possible to determine if gender or any other personal characteristic play a role in participants' inclination to follow financial advice provided by AI-based advisors. The information collected through the background questions served as control variables, providing valuable insights for interpreting, and contextualizing the survey responses within the broader participant demographic.

3.2 Sampling and Power Calculation

To determine the appropriate sample size for this study, an "a priori" power analysis was conducted based on effect sizes reported in relevant literature. Hancock et al. (2011) conducted a meta-analysis on trust in human-robot interactions, providing a quantitative synthesis grounded in empirical evidence. Their analysis revealed a significant experimental effect size of $d = +0.71$. Drawing from these findings, a power test calculation was performed using G-Power software and a two-sided Fisher Exact test to estimate the required number of survey responses. Detailed calculations can be found in Appendix A – Power Calculation. The analysis determined that a minimum of 228 responses would be necessary to achieve sufficient statistical power. The survey was administered via the Erasmus-Qualtrics platform and remained open for a duration of two weeks. Despite concerted efforts to achieve the desired sample size, the total number of complete responses collected amounted to 191, falling short of the intended target.

4. Results

In total 193 people participated in the survey; however, 2 people did not answer all questions hence these answers were excluded, and the study was developed based on the 191 complete observations. The dataset used in this study is composed of qualitative and quantitative information, which will be analysed separately in the following subsections of this chapter. The analysis was conducted using the software STATA and Excel.

While certain variables in this study, such as gender and country, possess a straightforward understanding, there are other variables that require closer examination.

- *Profile Variable*

Each respondent's risk profile was determined based on their responses to questions in the Lottery Block. These risk profiles were recorded in the database and will solely serve as control variables in the analyses. The risk profiles range from 1 to 5, with 1 representing a conservative profile and 5 representing an aggressive profile. As the profile number increases, there is a gradual decrease in the degree of risk aversion. This characteristic allows the risk profile to be treated as an ordinal variable, wherein each profile unit increment represents an increase in the risk tolerance of the respondent. The utilization of a continuous variable enables the calculation of statistical measurements and facilitates further analyses.

- *Trust Variable*

The trust factor, derived from participants' responses (in Likert scale) to the four trust statements, serves as a valuable variable for evaluating and comparing trust levels within the sample, supporting the investigation of trust-related decisions in this study. Each statement captures a distinct aspect of trust: the first statement (TS1) reflects overall trust in financial advice, the second (TS2) pertains to the belief in a conflict-free service, the third (TS3) relates to trust in the risk management strategy, and the fourth statement (TS4) assesses confidence in the accuracy of financial information.

By structuring all statements to positively express trust, the Likert scale consistently indicates higher levels of trust as respondents agree more strongly with each statement. Consequently, the responses to these four trust statements can be treated as scores, ranging from 1 to 5, with 5 indicating a higher degree of trust and 1 indicating a lack of trust. The use of this measurement approach makes possible to explore variations in trust levels across different groups and perform statistical analyses to gain insights into the role of trust in our study's context.

- The variable "Global Average Trust" was constructed for each participant by computing the simple average score of their responses to the four trust statements. This composite measure provides valuable insights into the overall level of trust exhibited by the participants in the study. *Demographic Characteristics Variables*

The variables Country and Gender indicated the country of residence of the respondent and the gender with it they identified themselves, these are categorical variables. The variables Age, Education, Financial Education, and Income were also derived from the responses obtained during the Background Questions Block. These specific questions were carefully designed to enable the assignment of meaningful numerical values to each category. During the survey, the response options for each question were presented in a specific order, always ranging from the lowest level to the highest level.

For instance, consider the question:

Please indicate the highest level of education you have completed.

1) *Below secondary school*
2) *Secondary education*
3) *Bachelor's degree*
4) *Master's degree*
5) *PhD or higher education*

With this approach, respondent respondents who selected a higher option number, such as 4, indicated a higher level of education compared to those who chose a lower option number, such as 3. The assigned numerical values effectively captured an increase in the variables, with higher category numbers corresponding to greater values of Age, Education, Financial Education, and Income.

This ordering scheme allows for the variables to be ordinal instead of categorical, which greatly facilitates the analysis and calculations by simplifying the interpretation. This adaptation was possible since these variables serve as control variables. The primary focus of this study is not to precisely quantify the exact magnitude of the effects these variables have on respondents' decisions, an understanding of the direction of these effects is sufficient.

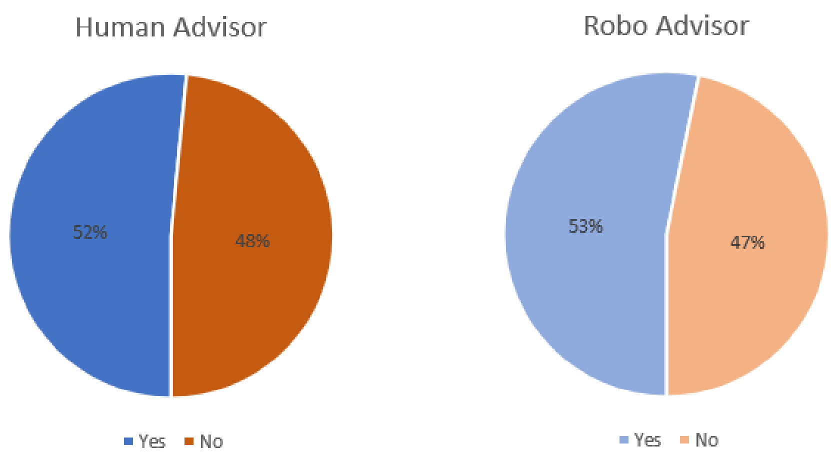
4.1 Summary Statistics

The data will be analysed from a macro perspective, treating risk profiles as a control variable rather than an explanatory one. Given that the focus of this study is to investigate the role of trust in the decision-making process of adopting financial advice from a Certified Financial Planner (CFP®) or a robot, rather than examining how an individual's risk profile influences their behaviour in this context. The identification and subdivision of participants' risk profiles ware done solely to reduce or even eliminate the potential influence of unsuitable investment recommendations as a decisive factor (e.g., participants with a conservative risk profile would not feel comfortable with a portfolio recommendation that could occur in losses, and conversely an investor with aggressive risk profile would not follow a low-risk portfolio recommendation). By providing investment recommendations that suit the respondents' risk profiles, the potential rejection due to misaligned recommendations is reduced. A detailed table containing descriptive statistics by profiles can be found in the Appendix B- Table 2.

In terms of gender distribution, the dataset exhibited relative homogeneity, with 49.22% of participants identifying as male and 50.78% as female. The average age of the respondents fell within the 41-46 years old range. Moreover, participants, on average, had completed a Master's degree as their highest level of education. Financial knowledge, as indicated by respondents, was at a medium level and the average income of participants corresponded to the category "Between €80.001 and €100.000 per year". The survey was completed by individuals hailing from 11 different countries; however, the majority of respondents resided in either Brazil (77.49%) or the Netherlands (15,18%).

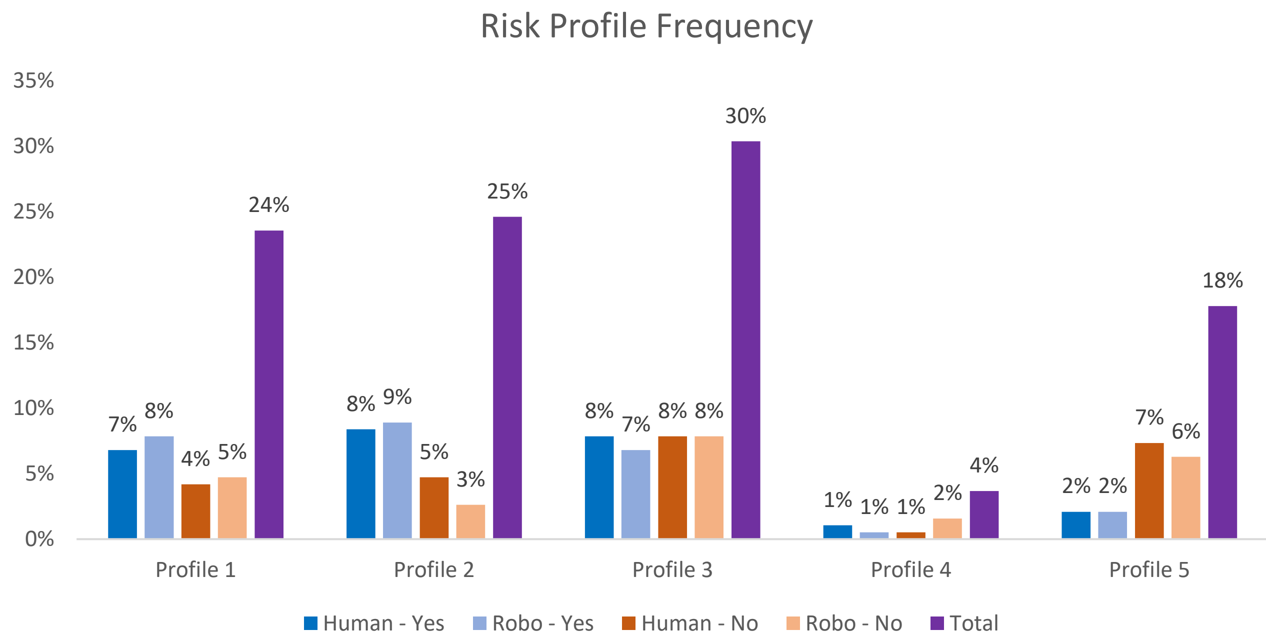
4.2 Main Results

Graph 1: Participants' Follow/Not Follow Percentage



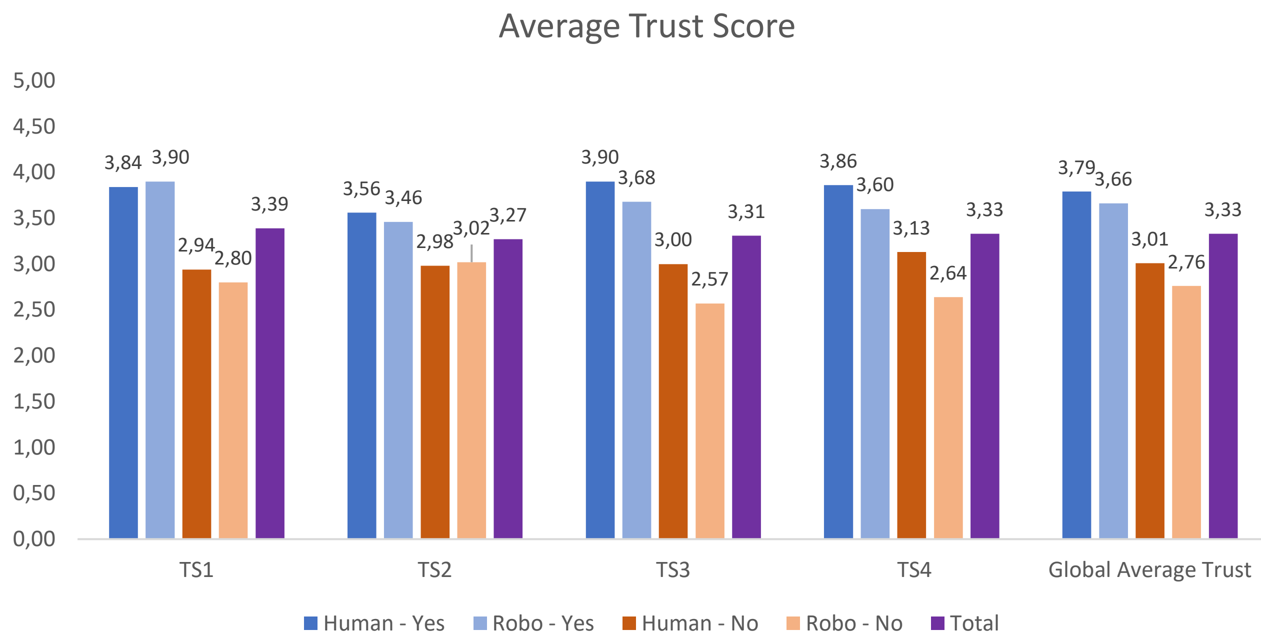
Among the 191 participants, a total of 97 individuals received financial advice from a Certified Financial Planner (CFP®), and out of these, 50 indicated their intention to follow the advice provided. Conversely, the remaining 94 participants received financial advice from a Robo-advisor, with an equal number of 50 expressing their intention to follow the advice.

Graph 2: Risk Profile Frequency



Notably, the moderate risk profile (3) was the most prevalent among the respondents, accounting for 30.37% of the sample, while the moderately aggressive profile (4) was the least common, representing only 3.67% of participants. On average, the overall risk profile of the entire sample ranged between moderately conservative (2) and moderate (3).

Graph 3: Average Trust Score



The highest average trust score was observed for the trust in the overall financial advice (3.39), whereas the lowest trust score was associated with the belief in a conflict-free service (3.27). The Global Average Trust score across all participants was 3.33.

Table 1 provides a descriptive overview of participant characteristics and trust levels, categorized into different groups (who received the financial advisory from a Human and who received it form from a Robo) and subgroups (who indicated that would follow the financial advice provided: "Yes"; and who indicated that would not follow it: "No"). The table with all descriptive statistics of the dataset can be found in Appendix B - Table 1.

Table 1: Descriptive Analysis of Profiles, Trust Levels and Gender.

	Human Advisor									
	Follow					Not Follow				
Variable	*n*	*Mean*	*Std. Dev.*	*Min*	*Max*	*n*	*Mean*	*Std. Dev.*	*Min*	*Max*
Risk Profile	50	2,36	1,1563	1	5	47	3,09	1,4571	1	5
TS1	50	3,84	0,8172	2	5	47	2,94	1,0715	1	5
TS2	50	3,56	0,9723	1	5	47	2,98	1,0732	1	5
TS3	50	3,90	0,7354	2	5	47	3,00	0,9780	1	4
TS4	50	3,84	0,7827	1	5	47	3,13	1,0758	1	4
Global Average Trust	50	3,79	0,6356	2,25	5	47	3,01	0,8024	1	4,25
Male	50	0,48	0,5047	0	1	47	0,45	0,5025	0	1

	Robo-Advisor									
	Follow					Not Follow				
Variable	*n*	*Mean*	*Std. Dev.*	*Min*	*Max*	*n*	*Mean*	*Std. Dev.*	*Min*	*Max*
Risk Profile	50	2,24	1,1528	1	5	44	3,09	1,4598	1	5
TS1	50	3,90	0,6468	2	5	44	2,80	1,1326	1	4
TS2	50	3,46	1,0343	1	5	44	3,02	1,1511	1	5
TS3	50	3,68	0,8192	2	5	44	2,57	1,1493	1	5
TS4	50	3,60	0,8571	2	5	44	2,64	1,1225	1	5
Global Average Trust	50	3,66	0,7031	2	5	44	2,76	0,9237	1	4,5
Male	50	0,50	0,0505	0	1	44	0,55	0,5037	0	1

Upon analysing the data in relation to the first research question and the first two hypotheses, several insights can be gleaned. Firstly, the analysis aimed to determine the influence of the financial provider's nature (Human/Robo) on individuals' decision to follow or disregard the provided financial advice.

Hypothesis 1 posited that overall, people are more inclined to follow the advice provided by a human financial advisor. However, the large p-value of Pearson's Chi-squared test ($p = 0.82$) revealed that the discrepancy between the number of individuals inclined to follow financial advice based on the nature of the provider is not significant. This suggests that people might no longer have strict preferences for human advisors over AI-based advisors in the realm of financial advisory services. This finding contradicts previous research and could be attributed to the recent advancements in AI technology that have garnered public attention.

Hypothesis 2 examined the role of risk profiles and personal characteristics in participants' inclination to follow financial advice provided by AI-based advisors. Surprisingly, the data revealed that individuals with riskier risk profiles exhibit a decreased inclination to follow the financial advice, irrespective of the nature of its advisor. In contrast, individuals with more conservative risk profiles demonstrate a greater inclination to follow financial advice, regardless of whether the advisor is human or AI-based. The results of Pearson's Chi-squared tests indicate that individuals' risk profiles have a significant impact on the decision to follow or not the advice provided when the advisor is a robot ($p = 0.012$), however this impact is not statistically significant for the human-advisor ($p=0.062$). These finding challenges initial expectations and highlights the complexity of the relationship between risk profiles and the acceptance of financial advice.

Furthermore, when considering demographic characteristics, such as gender and education level, there is no evident trend suggesting that a particular group is more or less inclined to follow the advice based on the provider's nature. However, a curious observation is that a slightly higher number of women and individuals with a bachelor's degree express a bigger reluctance to follow advice when the provider is a human. Further investigation is warranted to explore the underlying factors contributing to this observation.

It is important to note that the analysis is somewhat constrained by the high concentration of respondents residing in Brazil, with a relatively smaller proportion from The Netherlands and almost insignificant presence in other countries. This limited geographic diversity impedes comprehensive comparisons between different behavioural patterns associated with specific characteristics of each country.

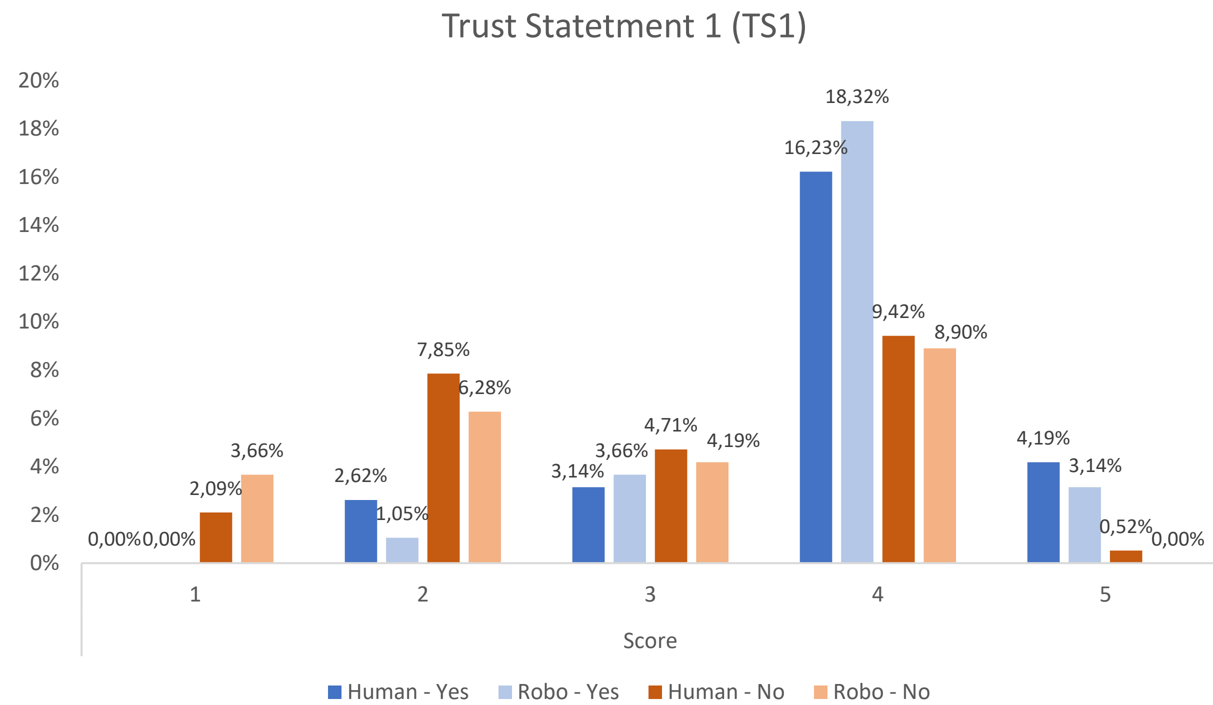
In summary, the analysis indicates that the nature of the financial advisor does not significantly influences individuals' decision to follow the advice provided or not, suggesting that respondents are potentially indifferent between the two types of providers. Risk profiles appears to have some influence in individuals' inclination to follow the advice, regardless of the provider's nature. However, personal characteristics (Pearson's Chi-squared result for gender $p = 0.95$; Fisher Exact Test results for age $p = 0.689$, financial education $p = 0.483$ and income $p = 0.417$) and geographic location (Fisher Exact Test results for country $p = 0.568$) do not seem to exert an impact on the inclination to follow the advice based on the provider's nature. Further research is needed to delve deeper into these dynamics and uncover the underlying mechanisms driving these findings.

The analysis of the data concerning the second research question and the third hypothesis reveals noteworthy insights into the role of trust as an obstacle to the adoption of AI-based financial advisory services. Specifically, we sought to investigate whether lack of trust significantly hinders the use of such services and if there is a particular aspect of trust that holds more prominence.

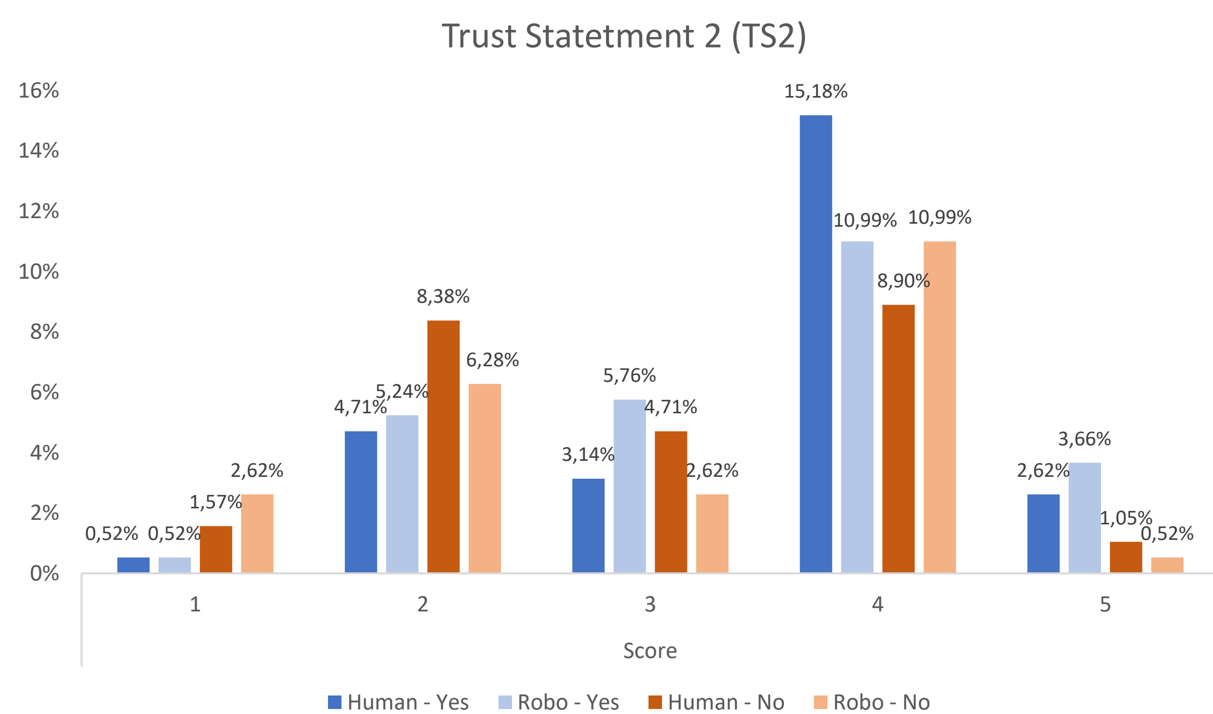
Upon comparing the responses of participants who received financial advice from a human and expressed reluctance to follow the advice, with those who received it from robot and indicated their non-adherence, it was found no significant difference that would suggest that the nature of the advisor influences participants' decision-making (Pearson's Chi-squared test p value = 0.82). However, delving deeper into the data revealed intriguing variations in trust indicators between these two groups.

To provide visual representations of these response patterns, graphical displays of the frequency distribution for each trust statement are presented below.

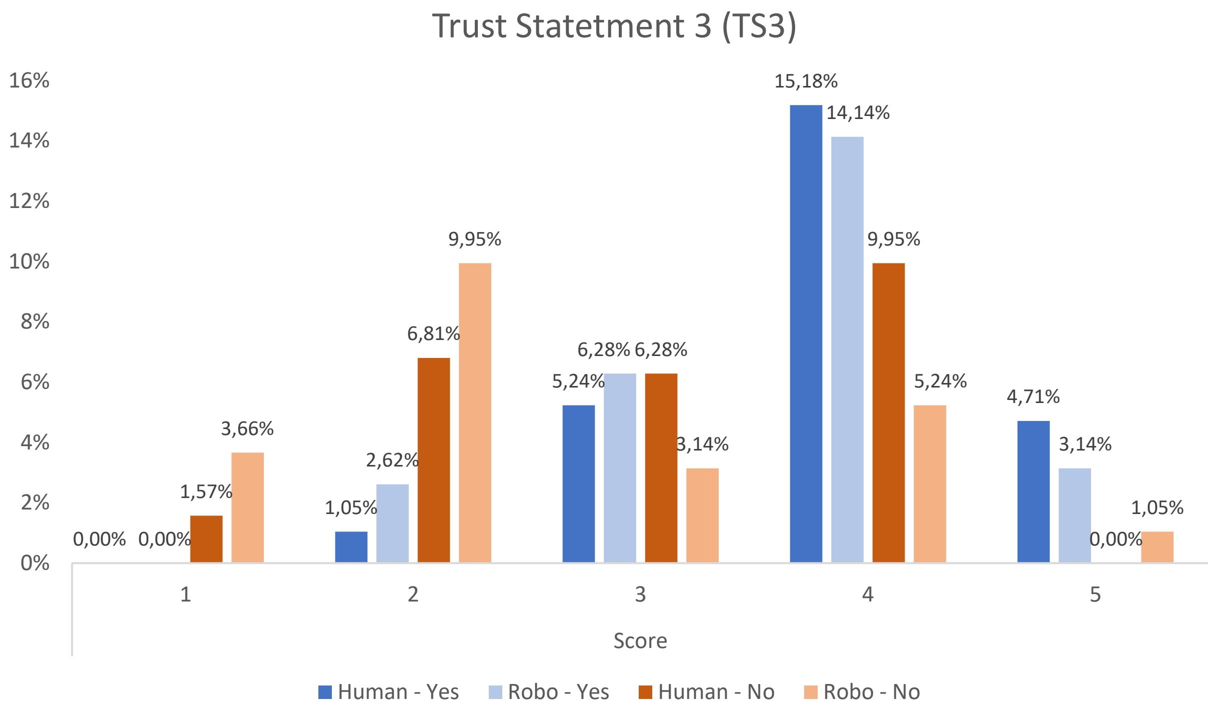
Graph 4: Trust Statement 1 Answers Frequency Distribution



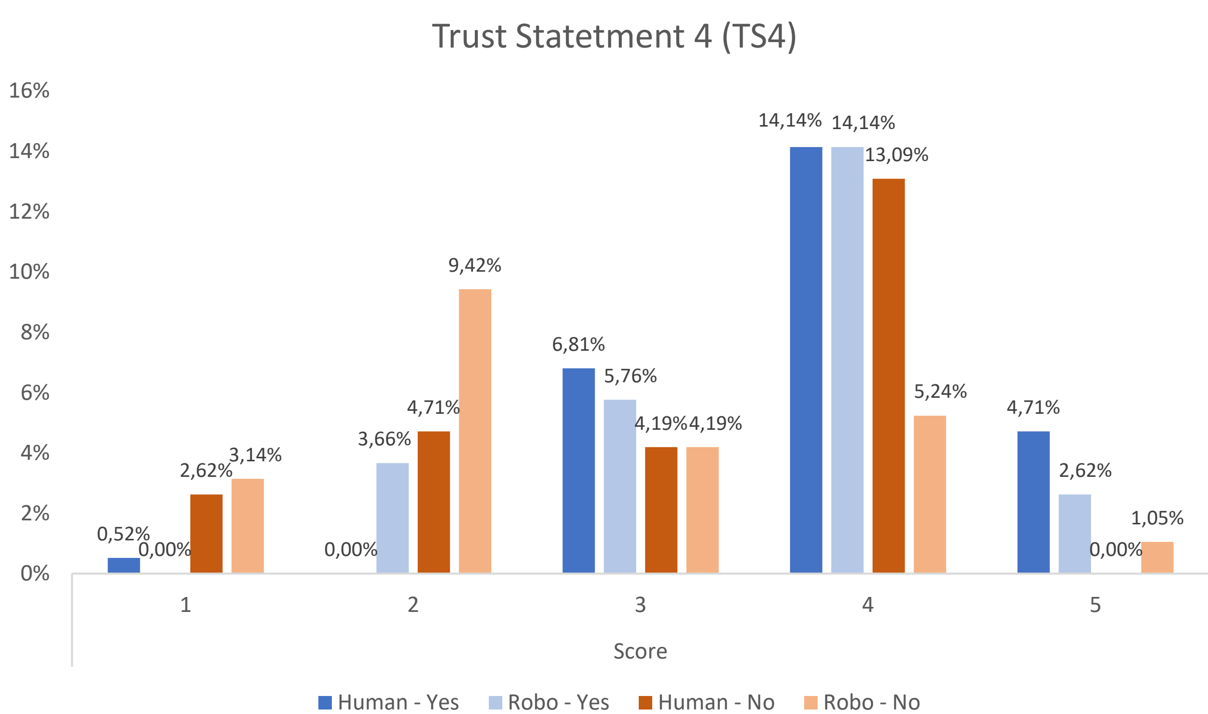
Graph 5: Trust Statement 2 Answers Frequency Distribution



Graph 6: Trust Statement 3 Answers Frequency Distribution



Graph 7: Trust Statement 4 Answers Frequency Distribution



Analysing the trust ratings based on the nature of the provider for respondents who expressed unwillingness to follow the financial advice provided, three out of the four trust statements received lower scores when the provider was a robot. It is worth noting that only Trust Statement 2 (TS2)[3], which pertains to the aspect of conflict-free services, received higher scores for the robo-advisor (3.02) compared to the human advisor (2.98).

The data suggests that, on average, participants in this survey place higher trust in human advisors than in robo-advisors, particularly concerning the overall financial advice (TS1), the risk management strategy (TS3), and the accuracy of information (TS4). Interestingly, when it comes to the exemption of conflicts of interest, the robo-advisor is perceived as more trustworthy.

To present these insights effectively, trust statement scores for all groups and decisions are presented in the table below:

Table 2: Descriptive Analysis of Trust Levels

	Human Advisor (97)		Robo-Advisor (94)		*Total*
	Yes (50)	No (47)	Yes (50)	No (44)	*(191)*
Global Average Trust	3,79	3,01	3,66	2,76	*3,33*
Average TS1	3,84	2,94	3,90	2,80	*3,39*
Average TS2	3,56	2,98	3,46	3,02	*3,27*
Average TS3	3,90	3,00	3,68	2,57	*3,31*
Average TS4	3,86	3,13	3,60	2,64	*3,33*

The average trust score represents the mean score of each respondent based on their answers to the four statements. Additionally, the global average trust score is the average trust score calculated for the entire sample and each group (Human/Robo; Yes/No), which enable broader analysis. Irrespective of their intention to follow the advice, participants who received financial advice from a human exhibit a slightly higher global average trust scores (Yes: 3.79; No: 3.01) compared to

[3] "I believe that this financial service provider has my best interests in mind."

those who received advice from a robot (Yes: 3.66; No: 2.76), the effects were found statistically significant (Pearson's Chi-squared test $p = 0.038$ and $p = 0.001$).

An observable pattern emerges from the analysis of participants' responses to the trust statements. Regardless of the provider, individuals who expressed their intention to follow the provided advice exhibited a tendency to concentrate their trust ratings around score 4, while scores 1 and 2 were less frequently chosen and, in some cases, even had a frequency of zero. For instance, in the robo/yes group, score 1 was absent in TS1, TS3, and TS4, and in the human/yes group, score 1 was absent in TS1 and TS3. Conversely, participants who stated that they would not follow the financial advice displayed a more evenly distributed frequency of trust ratings across different scores. Interestingly, it is notable that participants who received advice from a robo-advisor did not assign a score of 5 to TS1, and participants who received advice from a human advisor did not assign a score of 5 to TS3 and TS4.

In summary, a noteworthy observation is that participants who expressed an intention to follow the financial advice, irrespective of whether it was provided by a human or robot advisor, displayed significantly higher trust scores. Specifically, their trust scores were 16 and 17 percentage points higher (Human: 3.79; Robo: 3.66) compared to those who stated that they would not follow the advice (Human: 3.01; Robo: 2.76). This finding underscores the importance of trust as a critical factor influencing individuals' inclination to follow financial advice, regardless of the advisor's nature. Higher levels of trust appear to be closely associated with a greater likelihood of following the recommended guidance.

While these findings offer valuable insights into trust dynamics between human and robo-advisors, further research is necessary to comprehensively investigate and understand the underlying mechanisms driving these observed patterns.

4.2 Ordinary Least Squares (OLS) Analysis

To assess the impact of each variable on the likelihood of individuals following the provided financial advice, an Ordinary Least Squares (OLS) regression was conducted on the dataset. However, it is important to acknowledge that certain assumptions of OLS, such as the sample size or normally distributed variables, might not hold due to the nature of the dataset. Nevertheless, the purpose of the econometric regression is to check for the robustness of previous findings and potential direction of the coefficients.

Even though the dependent variable in the model is binary, representing whether participants would follow the financial advice (0) or not (1), the OLS regression was selected due to its straightforward interpretation compared to the Logit regression. To ensure the robustness of the results, a Logit regression was also conducted as a supplementary analysis. The independent variables of interest in this study are i) Global Average Trust; ii) Treatment, which indicates the nature of the financial advisor: Human (0) or Robot (1) and iii) an interaction term between the two representing the Global Average Trust for subjects who received advice from a robo-advisor (Treatment = 1).

It is worth noting that participants who responded "Prefer not to say" to the income question were excluded from the OLS regression, resulting in a model using 176 observations, with R^2 of 0.3552.

Table 3 – OLS Model.

R^2: 0.3552

OLS Regression - Dependent Variable: Follow/Not Follow Financial Advice					
Variable	Coefficient	t- statistics	P-Value	Confidence	Interval
Treatment	0,0506 (0,2281)	-0,2300	0,8190	-0,5028	0,3984
Global Average Trust	-0,2605*** (0,0506)	-5,1500	0,0000	-0,3605	-0,1605
Treatment##Global Average Trust	-0,0101 (0,0645)	-0,1600	0,8760	-0,1375	0,1173

Profile	0,0818** (0,0266)	3,0700	0,0030	0,0292	0,1344
Age	0,0148 (0,0159)	0,9300	0,3520	-0,0165	0,0462
Female	0,0360 (0,0756)	0,4800	0,6340	-0,1133	0,1853
Education	-0,1781** (0,0637)	-2,8000	0,0060	-0,3039	-0,0523
Financial Education	-0,0103 (0,0411)	-0,2500	0,8020	-0,0915	0,0708
Income	-0,0014 (0,0135)	-0,1100	0,9150	-0,0281	0,0252
Country (Brazil as reference)					
Netherlands	0,0020 (0,1002)	0,0200	0,9840	-0,1960	0,2001
USA	-0,1958 (0,1705)	-1,1500	0,2520	-0,5325	0,1409
Norway	0,2434** (0,0754)	3,2300	0,0020	0,0944	0,3925
Mexico	0,0507 (0,2256)	0,2200	0,8220	-0,3950	0,4964
Canada	-0,8830*** (0,1067)	-8,2800	0,0000	-1,0937	-0,6722
Spain	-0,2121** (0,0681)	-3,1200	0,0020	-0,3466	-0,0777
Denmark	0,5737*** (0,0921)	6,2300	0,0000	0,3918	0,7556
Greece	-0,3797*** (0,0975)	-3,8900	0,0000	-0,5723	-0,1871
Ireland	0,0300 (0,1125)	0,2700	0,7900	-0,1923	0,2523
New Caledonia	-0,4471*** (0,0898)	-4,9800	0,0000	-0,6245	-0,2697
Constant	1,7592*** (0,3374)	5,2100	0,0000	1,0927	2,4257

The OLS regression results confirm the patterns observed in the descriptive statistics. Only the Global Average Trust, Education, and Profile variables were found to be statistically significant. The coefficients for both Global Average Trust (-0,2605***) and Education (-0,1781**) were negative, indicating that higher levels of trust and education decrease the probability of a respondent stating that they would not follow the provided advice. Conversely, the coefficient for the Profile variable (0,0818**) was positive, suggesting that individuals with higher risk profiles are more inclined to disregard the financial advice provided.

The lack of statistical significance for the Interaction Term coefficient (-0,0101) aligns with the previous analysis, which indicated that the most notable differences in trust scores were associated with the decision to accept or reject the advice rather than the specific nature of the advisor. This suggests that trust in the advice itself plays a more influential role than the type of advisor in shaping individuals' inclination to follow the financial advice.

Similarly, the Treatment variable coefficient (0,0506), indicating the nature of the advisor (Human or Robo), was not found to be statistically significant in the regression analysis. This finding further supports the previous analysis, indicating that the distinction between human and AI-based advisors does not significantly impact individuals' likelihood to follow the provided financial advice. It reinforces the notion that trust in the advice itself, rather than the nature of the advisor, plays a more significant role in influencing individuals' decision-making.

Additionally, we observed significance in the constant term and specific countries compared to the reference country (Brazil). However, due to the discrepancy in the number of observations between Brazil and other countries, the analysis becomes inconsistent. To further examine the robustness of the OLS findings, a logit regression was also performed, the results did not change qualitatively and can be found in Appendix B – Table 3.

4.3 Qualitative Analysis

Among the 91 participants that would not follow the financial advice given, 48 of them provided their main reasons for this decision in response to the open-ended question. These 48 answers were analysed, and recurring topics emerged, forming the basis of the qualitative analysis in this study.

Despite variations in participants' wording, it was possible to categorize the comments into five distinct categories:

- *Trust*: This category includes answers in which participants mentioned a lack of trust as the main reason for not following the advice. Examples of answers falling into this category include statements such as "Because I do not know the advisor," "I would follow it if the advisor was recommended by someone I know," and straightforward statements like "Lack of trust."

- *Conflict of interests:* This category comprises answers that participants expressed concerns about the advisor's potential bias towards their own interests. For instance, participants raised issues such as “Financial advisors are often biased due to their own interests, and more often than not, will recommend investments with better profitability for themselves instead of providing the best options for the investor”.

- *Advice*: This category includes answers in which participants questioned the recommended assets and expressed reservations about the financial advice itself. Examples of answers in this category include statements such as "I would prefer to invest in something with dividends," "I prefer to have more options," and “Too risky investments”.

- *Suitability*: Answers falling into this category involve participants questioning the suitability of the advice for their specific risk profile or expressing concerns about the determination of their risk profile. Examples include statements such as “The risky asset is too risky, and the overall advice does not take into account other key information of my risk profile” and “As long as I do not meet my retirement goal, I have to prioritise the growth of my portfolio”.

- *Robo*: This category encompasses answers in which participants explicitly mentioned the robotic nature of the advisor as the primary reason for not following the advice. For instance, “I would rather talk to people than robots", "I trust more in people than in robots", and "Lack of understanding of AI based financial service".

Out of these 48 comments, 21 were provided by participants who received advice from the robo-advisor, while 27 were from participants who received advice from a human advisor. Overall, there were no expressive differences in the average profiles or demographic characteristics between the groups. For a detailed comparison, please refer to Appendix B – Table 4. Participants who explained why they would not follow the advice had an average risk profile of 3.38. The gender distribution was nearly equal, with 23 male participants and 25 female participants. The average age of participants ranged between 36 and 41 years. The majority of respondents had attained ate least Bachelor's or Master's degrees, possessed medium financial knowledge, and reported an average annual income between €80,001 and €100,000. Once again, the majority of respondents resided in Brazil (39), followed by The Netherlands (8), with Denmark (1) and Mexico (1) having a smaller representation.

Table 4 – Qualitative Analysis of Comments section

	Robo-Advisor (21)	Human Advisor (27)	*Total (48)*
Nature of Comment			
Trust	2	4	*6*
Conflict of interests	0	6	*6*
Advice	7	14	*21*
Suitability	5	3	*8*
Robo	7	0	*7*
Global Average Trust	2,40	3,02	*3,00*
Average T1	2,48	3,11	*2,83*
Average T2	2,81	2,93	*2,88*
Average T3	2,00	2,96	*2,54*
Average T4	2,33	3,07	*2,75*

It is worth emphasizing that the majority of participants' responses (60%) revolved around intrinsic characteristics of the financial advice and the determination of their risk profile, this finding highlights a limitation of both the survey and the current study. Nevertheless, further insights can be gleaned from the table provided above. Notably, none of the participants mentioned "conflict of interest" as a reason for not following the advice provided by a robo-advisor, whereas this factor was cited in 22% of the comments from respondents who would not follow the advice from a human advisor. As expected, not following the advice due to the provider being a robo-advisor was only surfaced in responses from participants who received guidance from a robot, constituting 33% of their stated reasons. Trust, on the other hand, was the least frequently discussed topic, being identified as primary reason in 9.5% of the comments from participants with robo-advisory services and in nearly 15% of the comments from participants with human-advisory services.

The data from this subset of the sample confirms the patterns observed in the descriptive statistics of the entire sample, specifically regarding the variations in trust levels across different advisor groups. Notably, when the financial advice was provided by a robo-advisor (2,40), the Global Average Trust decreased by more than 20 percentage points compared to when it was provided by a human advisor (3,02). This global behaviour is also noticed in the consistently lower average scores for each one of trust statements independently, suggesting a lower level of trust among participants who received advice from a robo-advisor.

Furthermore, the Global Average Trust among participants who expressed their reasons for not following the financial advice (3,00) was found to be 10 percentage points lower than the Global Average Trust of the full sample (3,33). This finding supports the well-known phenomenon where individuals are more likely to provide reasons when they are dissatisfied, indicated by a lower level of trust in this particular case.

5. Discussion and Limitations

5.1 Discussion

This thesis focuses on investigating the role of trust in the decision-making process and the factors that influence individuals' likelihood to follow the financial advice given by different types of advisors. The hypotheses explored the impact of risk profiles, demographic characteristics, and trust variables on individuals' inclination to follow the advice. Through a combination of quantitative and qualitative analysis, the study examines the relationship between trust, the nature of the advisor (human or robot), and individuals' decision-making regarding financial advice. The findings shed light on possible patterns and dynamics at play in the realm of financial advice and highlight the importance of trust in shaping individuals' decision-making.

Regarding individuals' inclination to follow or disregard the advice because of the nature of the provider, the study found a potential indifference between the two. This result goes against previous studies (Longoni et al., 2019 and Luo et al., 2019) that suggested a strong preference for human advisors. One possible explanation for this discrepancy could be the changing dynamics in the financial industry, with advancements in technology, increasing adoption of AI-based solutions and focus in enhancing consumer's experience (Gomber et al., 2018). Therefore, the indifference observed in this study might be a reflection of evolving consumer attitudes towards technology.

Aligned whit Kim, Cotwright, & Chatterjee (2019) findings, in terms of the influence of risk profiles on decision-making, the study found that individuals with riskier profiles were less likely to follow the provided financial advice. This suggests that individuals with higher risk tolerance might perceive themselves as more capable of making independent financial decisions and therefore rely less on advice from either human or robot advisors. On the other hand, individuals with lower risk tolerance might be more inclined to follow the advice provided, considering it a safer option.

The study also highlighted the importance of trust in individuals' decision-making. Participants generally exhibited higher trust in human advisors compared to robo-advisors, which is consistent with previous studies (Zang, Pentina & Fan, 2021). Robo-advisors, in contrast, were regarded as more trustworthy to provide conflict-free services, a perception rooted in individuals' assumptions of neutrality and objectivity of AI-based systems (Araujo et al.,2020). This finding suggests that individuals might prioritize different aspects of trust depending on the nature of the advisor. Trust in human advisors might be built on personal relationships, expertise, and face-to-face interactions, while trust in robo-advisors might stem from their perceived impartiality and lack of conflicts of interest. Additionally, participants who intended to follow the advice, regardless of the advisor, had higher trust scores. This suggests that trust plays a crucial role in individuals' decision to follow financial advice, regardless of the source.

Demographic characteristics such as gender, age, financial education, and income were found to not significantly influence individuals' inclination to follow advice based on the advisor's nature. However, higher education levels were associated with an increased likelihood of following the advice, irrespective of the advisor's nature. This challenges the traditional assumption that certain demographic groups prefer human advisors (Fulk, Watkins & Kruger, 2018). However, this study suggests that trust and risk profiles play a more substantial role in decision-making than demographic factors. Financial institutions and policymakers should prioritize building trust and tailoring advice to individual risk profiles rather than relying solely on demographic segmentation.

The qualitative analysis provided further insights into the reasons for disregarding financial advice, which aligned with the expected outcomes and existing literature. Concerns about the intrinsic characteristics of the advice and the determination of risk profiles were the primary reasons for disregarding advice. These findings highlight the need for banks to adopt smarter approaches, operating under more cost-effective models, and offering sophisticated, customized, and tailored services to meet the demands of this increasingly competitive and regulated market (Boustani, 2022). Once again, the issue of conflict of interest was predominantly associated with human advisors, suggesting that individuals perceive robo-advisors as more objective and less susceptible to personal gain. Consistent with the qualitative analysis, the insignificance of the interaction term in the ordinary least squares (OLS) model indicates that trust in the advice itself and its suitability exerted a more substantial impact on the decision to accept or reject the advice than the specific nature of the advisor.

This thesis has contributed with insights into factors guiding individuals' decisions and the role of trust in financial advisory services, particularly in the comparison between human and robo-advisors. By bridging the gap between the study's findings and the existing literature, this research advances our understanding of individuals' decision-making processes and offers practical insights for financial institutions and policymakers aiming to enhance their advisory services. The findings challenge the prevailing assumption of a strong preference for human advisors and instead suggest individuals to be indifferent between the two. This might be attributed to evolving consumer attitudes towards technology, in an increasingly digitized financial landscape with the broad adoption of AI-based solutions. Trust emerges as a critical factor in decision-making, with higher levels of trust associated with a greater inclination to follow advice, irrespective of the advisor's nature. Notably, the study emphasizes the importance of building trust in robo-advisors to enhance their usage. Addressing concerns related to trust, personalized recommendations, and determination of risk profiles is paramount for financial institutions and policymakers to cultivate trust in robo-advisory services, and thus should be the focus of future research.

5.2 Limitations

It is important to acknowledge the limitations of this study and consider how methodological choices and contextual factors might have influenced the data and study outcomes. Several limitations can be associated to constrains in its scope of self-reported data collected through an online survey. This method might be subject to response biases, such as social desirability bias or participants providing inaccurate information. Additionally, the use of a survey might have limited the depth of qualitative responses, potentially overlooking nuanced perspectives or reasons for decision-making.

The number of responses obtained was relatively small, which might restrict the generalizability of the findings to a broader population, restrain the use of econometric models and diminish the power of statistical analysis. Moreover, the absence of financial incentives to encourage participant engagement might have affected the level of interest and effort invested in the survey, potentially impacting the quality of the data. Another limitation is the simplified method used to determine participants' risk profiles, which depended on participants not making any mistakes when answering the questions and even though might not capture the full complexity of their risk preferences accurately. Future studies could incorporate longitudinal data collection method to provide a more robust understanding of individuals' decision-making processes and behaviours.

The study's limited geographic scope, primarily focusing on one country, hinders the generalizability of the findings to other regions and cultural contexts. Exploring cross-country comparisons could provide valuable insights into the influence of cultural and contextual factors on individuals' trust and preferences.

The exclusive distribution of the survey online introduces a selection bias, as it primarily captures individuals who are more open to using technology. This might result in an overrepresentation of individuals with positive attitudes towards robo-advisors, potentially skewing the results.

The lack of a comprehensive examination of the various components of trust, and the limited qualitative analysis of open-ended responses, possibly constrained the depth of understanding regarding participants' perceptions and experiences. Furthermore, self-response bias might be a concern, as participants might have provided socially desirable responses or might not be representative of the wider population. To further explore the role of trust in decision-making, future studies could experimentally manipulate trust factors, allowing for a controlled examination of the causal relationship between trust and decision-making outcomes.

Another limitation relates to the narrow focus on trust and risk profiles, neglecting other potential factors that could influence individuals' preferences and behaviours. Factors such as financial literacy, previous experiences with advisors, and personal attitudes towards technology could play significant roles. Future studies should consider a more comprehensive approach to capture a broader range of influential factors.

The study's experimental design, while providing valuable insights into decision-making processes, might not fully capture the complexities of real-world scenarios. Participants' behaviours and responses within a controlled experiment might differ from their actual behaviours in real-life financial decision-making situations, calling for consideration of the external validity of the findings. Complementing experimental findings with analysis of real-world data from financial institutions, such as anonymized transaction data, customer reviews, or satisfaction surveys, would bridge the gap between controlled experiments and real-world usage, providing deeper insights into the utilization of AI-based financial advisory services and their impact on financial outcomes.

Lastly, it is important to recognize that the open-ended question regarding the reasons for not following financial advice should have been presented only to respondents who indicated their intention not to follow advice and should have been placed before the trust-related questions. Even though this seems to be a small detail, it might have influenced participants' responses and introduced bias. Collecting qualitative data through interviews would offer a more nuanced understanding of participants' decision-making processes, capturing valuable insights not fully captured by surveys alone.

Acknowledging these limitations is essential for a comprehensive understanding of the study's findings. It also points to areas for future research and refinement of methodologies to address these limitations. The financial industry is rapidly evolving, with ongoing technological advancements and changing consumer attitudes, thus it should completely understand artificial intelligence and make its application more consummate (Makridakis, 2017). Therefore, the findings of this study might not hold true in the future. Recognizing the significance of trust in the financial advisory relationship goes beyond transactional benefits, as it instils a sense of security and confidence in clients' financial decisions, reducing anxieties about uncertainty and risks associated with investing in the financial market.

6. Conclusion

This thesis aimed to investigate factors that might influence investor’s decision to follow or disregard a financial advice provided by humans or robots. Data was collected through an online survey that ensured participants confidentiality and anonymity; all ethical standards were meet.

The study included participants from diverse countries and linguistic backgrounds by offering the survey in English and Portuguese.

A total of 191 observations, consisting of qualitative and quantitative information, were analysed separately using STATA and Excel. The independent variables considered included the advisor's nature, participants' risk profile, trust variables and demographic characteristics. The study focused on understanding the effects of these variables on decision-making, with the dependent variable representing respondents' willingness to follow financial advice.

When compared to previous findings, the descriptive statistics suggested individuals to be indifferent between human and robot advisors. Risk profiles were found to influence individuals' inclination to follow financial advice, with riskier profiles being less likely to follow advice. Personal characteristics such as gender and education did not present a representative impact on the inclination to follow advice based on the advisor's nature. Participants generally exhibited higher trust in human advisors, while robo-advisors were perceived as more trustworthy only in terms of conflict-free services. Regardless of the advisor, participants intending to follow the advice displayed higher trust scores.

The OLS regression analysis confirmed the trends observed in the descriptive statistics, with only three variables—Global Average Trust, Education, and Profile—being statistically significant. Higher levels of trust and education were associated with an increased likelihood of following the advice. Conversely, individuals with higher risk profiles were more inclined to disregard the financial advice provided. The lack of statistical significance for the Interaction Term coefficient indicated that trust in the advice itself played a more significant role than the specific nature of the advisor. Similarly, the nature of the advisor (human or robot) by itself did not significantly influence the likelihood of following the advice, underscoring the importance of trust in shaping decision-making.

Qualitative analysis of open-ended survey responses revealed respondents' reasons for disregarding the advice. Concerns primarily revolved around intrinsic characteristics of the financial advice and the determination of risk profiles, highlighting limitations of the survey and study. Concerns about conflicts of interest were expressed only by participants who received advice from humans, and a third of respondents who received advice from robo-advisors mentioned the nature of the advisor as the primary reason for disregarding it. Additionally, participants expressing reasons for not following the advice displayed lower trust levels compared to trust levels of the full sample, supporting the notion that individuals are more likely to provide reasons when they are dissatisfied, as indicated by a lower level of trust in this particular case.

This research contributes to the existing literature on human-robot interaction, providing insights into individuals' current behaviour and the significance of trust in the decision-making process. The study offers implications for financial institutions and policymakers aiming to enhance their advisory services. Future studies could explore additional factors influencing decision-making, such as tailored suitability questionnaires or the impact of personalized recommendations, to further deepen our understanding of individuals' preferences and trust dynamics in the evolving landscape of financial advice. By exploring and addressing these factors, we can work towards providing more tailored and effective financial advice that meets the diverse needs of individuals in an increasingly digital world.

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8. Appendix

8.1 Appendix A

Survey

Start of Block

Por favor selecione o idioma desejado na caixa ao lado. / Please select the desired language in the box on the side.

Dear Participant,
Thank you for entering the link of this survey!

I'm a Master's student of Behavioural Economics from the Erasmus University of Rotterdam, conducting a short survey for my thesis composed of hypothetical situations followed by some questions. It takes only 5-10 minutes!

For the success of the study, it is important that you fill out the questionnaire honestly, completely and to your best knowledge.

All portfolio recommendations and risk analysis are made based on actual financial planning rules.

All data is collected anonymously and will be kept strictly confidential. In case you have any questions, you can contact me through 650183yh@student.eur.nl.

I hereby agree to the terms and conditions of this survey and confirm that I am over 18 years of age.

- ○ I agree. (1)
- ○ I disagree. (2)

End of Block

Start of Block: Q1

You received a voucher of €100.00 to play one of the two lotteries described below. Which of the following options would you choose?

○ Play the lottery in which you have 75% of chance of receiving €70.00 and 25% of chance of receiving €130.00. (1)

○ Play the lottery in which you have 50% of chance of receiving €40.00 and 50% of chance of receiving €150.00. (2)

End of Block: Q1

Start of Block: Q2.0

Please answer the following question independently of the previous one.

You received a voucher of €100.00 to play one of the two lotteries described below. Which of the following options would you choose?

○ Receive €75.00 for sure, and do not play a lottery. (1)

○ Play the lottery in which you have 75% of chance of receiving €70.00 and 25% of chance of receiving €130.00. (2)

End of Block: Q2.0

Start of Block: Q2.1

Please answer the following question independently of the previous one.

You received a voucher of €100.00 to play one of the two lotteries described below. Which of the following options would you choose?

◯ Play the lottery in which you have 50% of chance of receiving €40.00 and 50% of chance of receiving €150.00. (1)

◯ Play the lottery in which you have 80% of chance of receiving €2.00 and 20% of chance of receiving €500.00. (2)

End of Block: Q2.1

Start of Block: Q3

Please answer the following question independently of the previous one.

You received a voucher of €100.00 to play one of the two lotteries described below. Which of the following options would you choose?

◯ Play the lottery in which you have 70% of chance of receiving €35.00 and 30% of chance of receiving €250.00. (1)

◯ Play the lottery in which you have 80% of chance of receiving €2.00 and 20% of chance of receiving €500.00. (2)

End of Block: Q3

Start of Block: Profile 1 (Conservative) robot

Please answer the following question independently of the previous one.

Imagine you have €1,000.00 that you want to invest and you receive the following message:

Hi.
My name is Augustus, I'm an AI-based financial advisory (robot) and I would like to recommend a portfolio investment for you.
I draw your risk profile based on the answers you provided previously, I believe you should invest 100% of this amount (€1,000.00) in an asset without risk. Applying in this asset, by the end of 12 months you will have €1,050.00 (5% return rate).

Would you follow the financial advice provided by Augustus, an AI-based financial advisory (robot)?

○ Yes. (1)

○ No. (2)

End of Block: Profile 1 (Conservative) robot

Start of Block: Profile 1 (Conservative) human

Please answer the following question independently of the previous one.

Imagine you have €1,000.00 that you want to invest and you receive the following message:

Hi.
My name is Augustus, I'm a Certified Financial Planner (CFP®) and I would like to recommend a portfolio investment for you.
I draw your risk profile based on the answers you provided previously, I believe you should invest 100% of this amount (€1,000.00) in an asset without risk. Applying in this asset, by the end of 12 months you will have €1,050.00 (5% return rate).

Would you follow the financial advice provided by Augustus, a Certified Financial Planner (CFP®)?

○ Yes. (1)

○ No. (2)

End of Block: Profile 1 (Conservative) human

Start of Block: Profile 2 (Moderately Conservative) robot

Please answer the following question independently of the previous one.

Imagine you have €1,000.00 that you want to invest and you receive the following message:

Hi.
My name is Augustus, I’m an AI-based financial advisory (robot) and I would like to recommend a portfolio investment for you.
I draw your risk profile based on the answers you provided previously, I believe you should invest 85% of this amount (€850.00) in an asset without risk. Applying in this asset, by the end of 12 months you will have €892.50 (5% return rate).
The other 15% (€150.00) should be invested in an asset with risk which, by the end of 12 months, can reach the value of €225.00 (+50% return rate) or decrease to €75.00 (-50% return rate) with equal probability.

Would you follow the financial advice provided by Augustus, an AI-based financial advisory (robot)?

○ Yes. (1)

○ No. (2)

End of Block: Profile 2 (Moderately Conservative) robot

Start of Block: Profile 2 (Moderately Conservative) human

Please answer the following question independently of the previous one.

Imagine you have €1,000.00 that you want to invest and you receive the following message:

Hi.
My name is Augustus, I’m a Certified Financial Planner (CFP®) and I would like to recommend a portfolio investment for you.
I draw your risk profile based on the answers you provided previously, I believe you should invest 85% of this amount (€850.00) in an asset without risk. Applying in this asset, by the end of 12 months you will have €892.50 (5% return rate).
The other 15% (€150.00) should be invested in an asset with risk which, by the end of 12 months, can reach the value of €225.00 (+50% return rate) or decrease to €75.00 (-50% return rate) with equal probability.

Would you follow the financial advice provided by Augustus, a Certified Financial Planner (CFP®)?

○ Yes. (1)

○ No. (2)

End of Block: Profile 2 (Moderately Conservative) human

Start of Block: Profile 3 (Moderate) robot

Please answer the following question independently of the previous one.

Congratulations, you've just won €1,000.00 !!

My name is Augustus, I'm an AI-based financial advisory (robot) and I would like to recommend a portfolio investment for you.
I draw your risk profile based on the answers you provided previously, I believe you should invest 70% of this amount (€700.00) in an asset without risk. Applying in this asset, by the end of 12 months you will have €735.00 (5% return rate).
The other 30% (€300.00) should be invested in an asset with risk which, by the end of 12 months, can reach the value of €450.00 (+50% return rate) or decrease to €150.00 (-50% return rate) with equal probability.

Would you follow the financial advice provided by Augustus, an AI-based financial advisory (robot)?

○ Yes. (1)

○ No. (2)

End of Block: Profile 3 (Moderate) robot

Start of Block: Profile 3 (Moderate) human

Please answer the following question independently of the previous one.

Imagine you have €1,000.00 that you want to invest and you receive the following message:

Hi.
My name is Augustus, I’m a Certified Financial Planner (CFP®) and I would like to recommend a portfolio investment for you.
I draw your risk profile based on the answers you provided previously, I believe you should invest 70% of this amount (€700.00) in an asset without risk. Applying in this asset, by the end of 12 months you will have €735.00 (5% return rate).
The other 30% (€300.00) should be invested in an asset with risk which, by the end of 12 months, can reach the value of €450.00 (+50% return rate) or decrease to €150.00 (-50% return rate) with equal probability.

Would you follow the financial advice provided by Augustus, a Certified Financial Planner (CFP®)?

○ Yes. (1)

○ No. (2)

End of Block: Profile 3 (Moderate) human

Start of Block: Profile 4 (Moderately Aggressive) robot

Please answer the following question independently of the previous one.

Imagine you have €1,000.00 that you want to invest and you receive the following message:

Hi.
My name is Augustus, I’m an AI-based financial advisory (robot) and I would like to recommend a portfolio investment for you.
I draw your risk profile based on the answers you provided previously, I believe you should invest 55% of this amount (€550.00) in an asset without risk. Applying in this asset, by the end of 12 months you will have €577.50 (5% return rate).
The other 45% (€450.00) should be invested in an asset with risk which, by the end of 12 months, can reach the value of €675.00 (+50% return rate) or decrease to €225.00 (-50% return rate) with equal probability.

Would you follow the financial advice provided by Augustus, an AI-based financial advisory (robot)?

◯ Yes. (1)

◯ No. (2)

End of Block: Profile 4 (Moderately Aggressive) robot

Start of Block: Profile 4 (Moderately Aggressive) human

Please answer the following question independently of the previous one.

Imagine you have €1,000.00 that you want to invest and you receive the following message:

Hi.
My name is Augustus, I'm a Certified Financial Planner (CFP®) and I would like to recommend a portfolio investment for you.
I draw your risk profile based on the answers you provided previously, I believe you should invest 55% of this amount (€550.00) in an asset without risk. Applying in this asset, by the end of 12 months you will have €577.50 (5% return rate).
The other 45% (€450.00) should be invested in an asset with risk which, by the end of 12 months, can reach the value of €675.00 (+50% return rate) or decrease to €225.00 (-50% return rate) with equal probability.

Would you follow the financial advice provided by Augustus, a Certified Financial Planner (CFP®)?

◯ Yes. (1)

◯ No. (2)

End of Block: Profile 4 (Moderately Aggressive) human

Start of Block: Profile 5 (Aggressive) robot

Please answer the following question independently of the previous one.

Imagine you have €1,000.00 that you want to invest and you receive the following message:

Hi.
My name is Augustus, I’m an AI-based financial advisory (robot) and I would like to recommend a portfolio investment for you.
I draw your risk profile based on the answers you provided previously, I believe you should invest 40% of this amount (€400.00) in an asset without risk. Applying in this asset, by the end of 12 months you will have €420.00 (5% return rate).
The other 60% (€600.00) should be invested in an asset with risk which, by the end of 12 months, can reach the value of €900.00 (+50% return rate) or decrease to €300.00 (-50% return rate) with equal probability.

Would you follow the financial advice provided by Augustus, an AI-based financial advisory (robot)?

○ Yes. (1)

○ No. (2)

End of Block: Profile 5 (Aggressive) robot

Start of Block: Profile 5 (Aggressive) human

Please answer the following question independently of the previous one.

Imagine you have €1,000.00 that you want to invest and you receive the following message:

Hi.
My name is Augustus, I’m a Certified Financial Planner (CFP®) and I would like to recommend a portfolio investment for you.
I draw your risk profile based on the answers you provided previously, I believe you should invest 40% of this amount (€400.00) in an asset without risk. Applying in this asset, by the end of 12 months you will have €420.00 (5% return rate).
The other 60% (€600.00) should be invested in an asset with risk which, by the end of 12 months, can reach the value of €900.00 (+50% return rate) or decrease to €300.00 (-50% return rate) with equal probability.

Would you follow the financial advice provided by Augustus, a Certified Financial Planner (CFP®)?

- ◯ Yes. (1)
- ◯ No. (2)

End of Block: Profile 5 (Aggressive) human

Start of Block: Trust Block

Please indicate at what level you agree or disagree with the following statements.

From 1 (strongly disagree) to 5 (strongly agree).

Overall, I feel I can trust the financial advice provided.

- ◯ 1. Strongly Disagree (1)
- ◯ 2. Partially Disagree (2)
- ◯ 3.Neutral (3)
- ◯ 4. Partially Agree (4)
- ◯ 5. Strongly Agree (5)

I believe that this financial service provider has my best interests in mind.

- ◯ 1. Strongly Disagree (1)
- ◯ 2. Partially Disagree (2)
- ◯ 3.Neutral (3)
- ◯ 4. Partially Agree (4)
- ◯ 5. Strongly Agree (5)

I trust the risk management strategies of the financial advice provided.

- ◯ 1. Strongly Disagree (1)
- ◯ 2. Partially Disagree (2)
- ◯ 3.Neutral (3)
- ◯ 4. Partially Agree (4)
- ◯ 5. Strongly Agree (5)

I am confident of the accuracy of the financial information provided by this service.

- ◯ 1. Strongly Disagree (1)
- ◯ 2. Partially Disagree (2)
- ◯ 3.Neutral (3)
- ◯ 4. Partially Agree (4)
- ◯ 5. Strongly Agree (5)

If you chose not to use this service, could you state one main reason for your choice? Otherwise please skip this question.

____

End of Block: Trust Block

Start of Block: Background Block

Please select your age range.

- 18-23 years. (1)
- 24-29 years. (2)
- 30-35 years. (3)
- 36-41 years. (4)
- 42-47 years. (5)
- 48-53 years. (6)
- 54-59 years. (7)
- 60-65 years. (8)
- 65-70 years. (9)
- 71-76 years. (10)
- 77+ years. (11)

Please select the gender that you identify yourself with.

◯ Male. (1)

◯ Female. (2)

◯ Non-binary/third gender. (3)

◯ Prefer not to say. (4)

Please insert your country of residence.

____

Please indicate the highest level of education you have completed.

◯ Below secondary school. (1)

◯ Secondary education. (2)

◯ Bachelor’s degree. (3)

◯ Master’s degree. (4)

◯ PhD or higher education. (5)

Please indicate the level of financial education/knowledge you believe you have.

◯ No knowledge at all. (1)

◯ Low knowledge. (2)

◯ Medium knowledge. (3)

◯ High knowledge. (4)

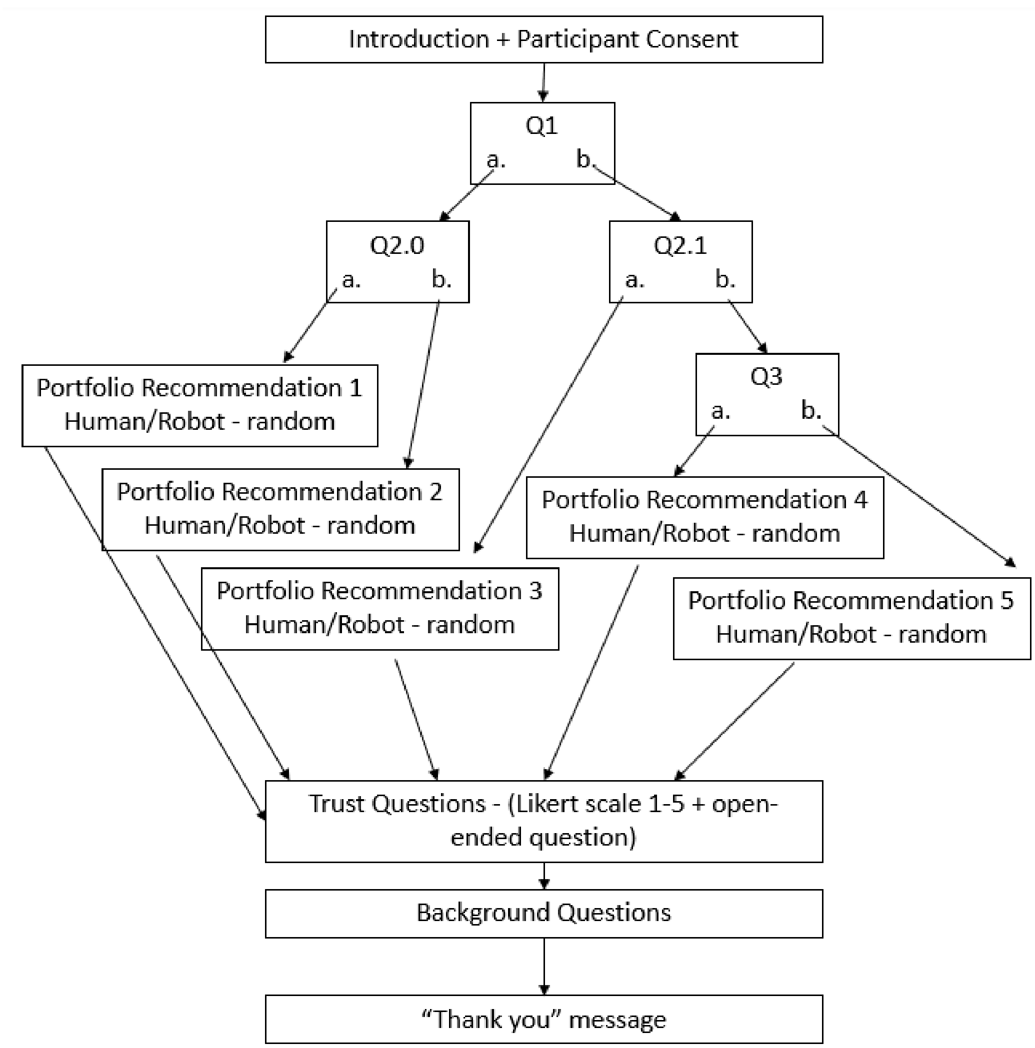
◯ Professional knowledge. (5)

Please select your approximate income per year (use the most recent estimation you have).

- Between €0 and €20.000 per year. (1)
- Between €20.001 and €40.000 per year. (2)
- Between €40.001 and €60.000 per year. (3)
- Between €60.001 and €80.000 per year. (4)
- Between €80.001 and €100.000 per year. (5)
- Between €100.001 and €120.000 per year. (6)
- Between €120.001 and €140.000 per year. (7)
- Between €140.001 and €160.000 per year. (8)
- More than €160.001 per year. (9)
- Prefer not to say. (10)

End of Block: Background Block

Survey Logic Flow:



Lottery Questions Design:

Q1

	Gain ($)	Probability (%)	Gain ($)	Probability (%)	Expected Value
A. Moderately Conservative	70.00	0.75	130.00	0.25	$ 85.00
B. Moderate	40.00	0.50	150.00	0.50	$ 95.00

Q2.0

	Gain ($)	Probability (%)	Gain ($)	Probability (%)	Expected Value
A. Conservative	75.00	1			$ 75.00
B. Moderately Conservative	70.00	0.75	130.00	0.25	$ 85.00

Q2.1

	Gain ($)	Probability (%)	Gain ($)	Probability (%)	Expected Value
A. Moderate	40.00	0.50	150.00	0.50	$ 95.00
B. Aggressive	2.00	0.80	500.00	0.20	$ 101.60

Q3

	Gain ($)	Probability (%)	Gain ($)	Probability (%)	Expected Value
A. Moderately Aggressive	35.00	0.70	250.00	0.30	$ 99.50
B. Aggressive	2.00	0.80	500.00	0.20	$ 101.60

Financial Advice Design:

Principal € 1.000,00

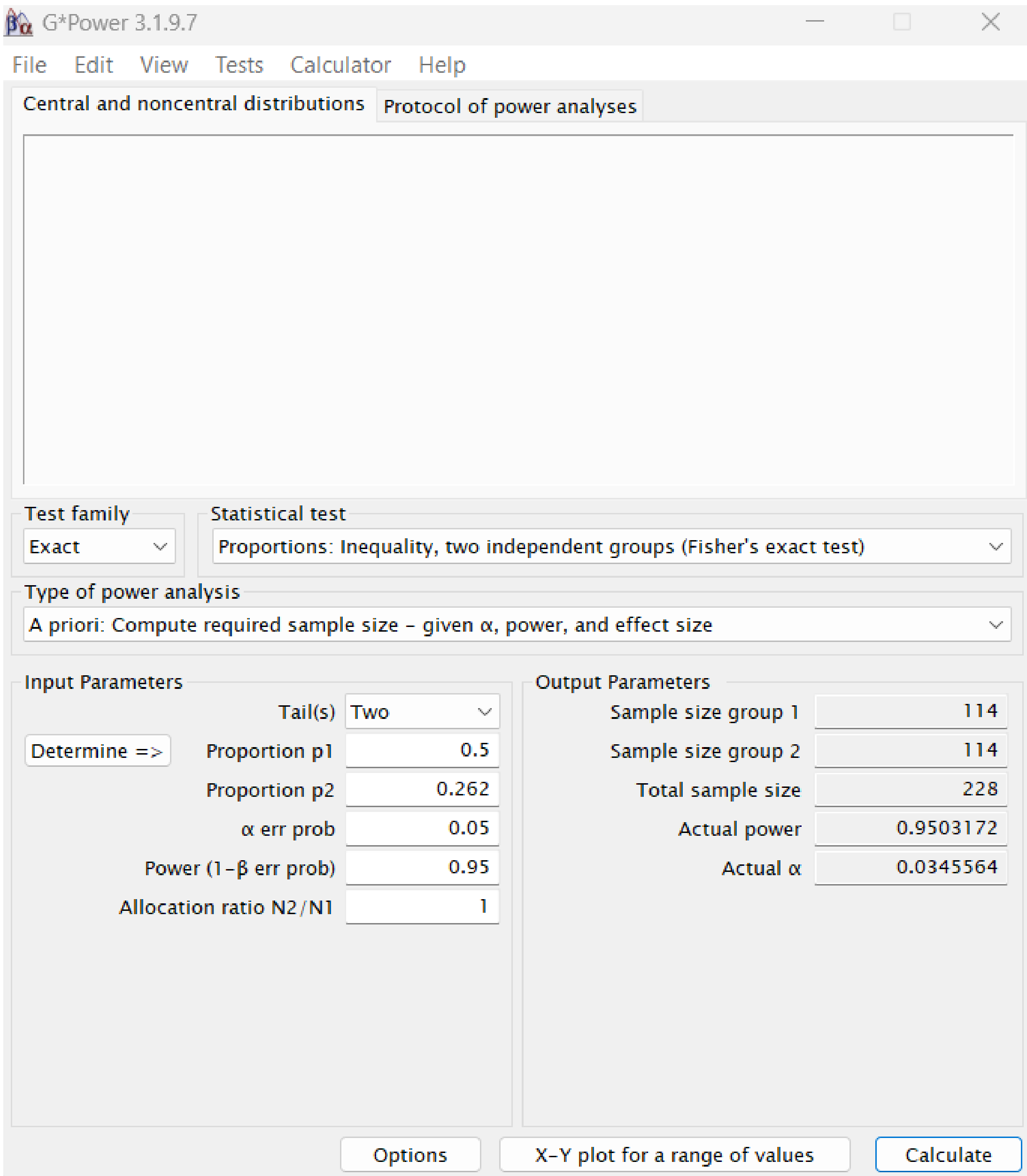
Profile	Risk Free Allocation	Return Rate	Risky Asset Allocation	Return -	Return +
1. Conservative	100%	5%	0%	-50%	50%
2. Moderately Conservative	85%	5%	15%	-50%	50%
3. Moderate	70%	5%	30%	-50%	50%
4. Moderately Aggressive	55%	5%	45%	-50%	50%
5. Aggressive	40%	5%	60%	-50%	50%

Principal R$ 1.000,00

Profile	Risk Free Allocation	Return Rate	Risky Asset Allocation	Return -	Return +
1. Conservative	100%	13%	0%	-50%	50%
2. Moderately Conservative	85%	13%	15%	-50%	50%
3. Moderate	70%	13%	30%	-50%	50%
4. Moderately Aggressive	55%	13%	45%	-50%	50%
5. Aggressive	40%	13%	60%	-50%	50%

Power Calculation:

Significance level (α) of 5%, the power of the test (1-β) of 0.95, the effect size of 0.71 and assuming that control and treatment group will have the same variance, for a 2-sided Fisher Exact test.



8.2 Appendix B

Table 1: Descriptive Analysis of Participants Characteristics and Trust Levels

	Human Advisor (97)		Robot Advisor (94)		*Total*
	Yes (50)	No (47)	Yes (50)	No (44)	*(191)*
Average Profile	2,36	3,09	2,24	3,09	*2,66*
Profile 1	13	8	15	9	*45*
Profile 2	16	9	17	5	*47*
Profile 3	15	15	13	15	*58*
Profile 4	2	1	1	3	*7*
Profile 5	4	14	4	12	*34*
Average Global Trust	3,79	3,01	3,66	2,76	*3,33*
Average TS1	3,84	2,94	3,90	2,80	*3,39*
Average TS2	3,56	2,98	3,46	3,02	*3,27*
Average TS3	3,90	3,00	3,68	2,57	*3,31*
Average TS4	3,86	3,13	3,60	2,64	*3,33*
Gender					
Male	24	21	25	24	*94*
Female	26	26	25	20	*97*
Age					
18-23 years	0	1	1	0	*2*
24-29 years	9	7	5	6	*27*
30-35 years	13	13	12	11	*49*
36-41 years	12	5	8	9	*34*
41-47 years	1	3	4	0	*8*
48-53 years	3	3	3	4	*13*
54-59 years	3	3	7	2	*15*
60-65 years	6	7	4	6	*23*
66-71 years	2	4	2	5	*13*
71-77 years	1	1	4	1	*7*
77+ years	0	0	0	0	*0*
Country					
Brazil	40	32	38	38	*148*
Netherlands	7	10	9	3	*29*
USA	0	1	2	0	*3*
Canada	1	0	0	1	*2*
Norway	0	1	0	1	*2*
Denmark	0	1	0	0	*1*
Ireland	0	0	0	1	*1*
Spain	1	0	0	0	*1*
Greece	1	0	0	0	*1*
Mexico	0	2	0	0	*2*
New Caledonia	0	0	1	0	*1*
Education Level					

Below secondary school	0	0	0	0	*0*
Secondary education	0	0	3	1	*4*
Bachelor's degree	14	25	16	17	*72*
Master's degree	35	21	30	25	*111*
PhD or higher education	1	1	1	1	*4*
Financial Education Level					
No knowledge at all	3	0	0	1	*4*
Low knowledge	11	13	15	13	*52*
Medium knowledge	22	25	25	25	*97*
High knowledge	8	6	5	3	*22*
Professional knowledge	6	3	5	2	*16*
Income					
Between €0 and €20.000 per year	6	7	6	2	*21*
Between €20.001 and €40.000 per year	4	1	2	3	*10*
Between €40.001 and €60.000 per year	6	2	4	6	*18*
Between €60.001 and €80.000 per year	5	12	5	10	*32*
Between €80.001 and €100.000 per year	5	3	7	3	*18*
Between €100.001 and €120.000 per year	4	4	2	0	*10*
Between €120.001 and €140.000 per year	2	3	4	4	*13*
Between €140.001 and €160.000 per year	2	1	4	2	*9*
More than €160.001 per year	12	11	13	9	*45*
Prefer not to say	4	3	3	5	*15*

Table 2- Descriptive Statistics of the full sample.

	N	Ave. Trust	Ave. TS1	Ave. TS2	Ave. TS3	Ave. TS4	Male	Female	Ave Age.	Ave. Education	Ave. Financial Education	Ave. Income per year
Profile 1	**45**	**3.44**	**3.44**	**3.38**	**3.40**	**3.56**	**19**	**26**	42-47 y	Master	Medium	€100.001 - €120.000
Robo	24	3.26	3.50	3.08	3.25	3.21	10	14	42-47 y	Master	Medium	€100.001 - €120.000
Yes	15	3.48	3.80	3.13	3.47	3.53	7	8	36-41 y	Master	Medium	€120.001 - €140.000
No	9	2.89	3.00	3.00	2.89	2.67	3	6	42-47 y	Master	Medium	€100.001 - €120.000
Human	21	3.65	3.38	3.71	3.57	3.95	9	12	42-47 y	Bachelor	Medium	€80.001 - €100.000
Yes	13	3.98	4.08	3.77	3.92	4.15	7	6	42-47 y	Master	Medium	€100.001 - €120.000
No	8	3.13	2.25	3.63	3.00	3.63	2	6	36-41 y	Bachelor	Medium	€80.001 - €100.000
Profile 2	**47**	**3.45**	**3.53**	**3.30**	**3.53**	**3.45**	**23**	**24**	36-41 y	Master	Medium	€60.001 - €80.000
Robo	22	3.42	3.59	3.27	3.36	3.45	12	10	42-47 y	Master	Medium	€60.001 - €80.000
Yes	17	3.69	4.00	3.41	3.65	3.71	8	9	42-47 y	Master	Medium	€80.001 - €100.000
No	5	2.50	2.20	2.80	2.40	2.60	4	1	36-41 y	Bachelor	Medium	€60.001 - €80.000
Human	25	3.48	3.48	3.32	3.68	3.44	11	14	36-41 y	Master	Medium	€60.001 - €80.000
Yes	16	3.80	3.88	3.56	3.94	3.81	7	9	36-41 y	Master	Medium	€60.001 - €80.000
No	9	2.92	2.78	2.89	3.22	2.88	4	5	36-41 y	Master	Medium	€60.001 - €80.000
Profile 3	**58**	**3.34**	**3.47**	**3.33**	**3.62**	**3.19**	**31**	**27**	48-53 y	Master	Medium	€100.001 - €120.000
Robo	28	3.31	3.36	3.50	3.32	3.07	15	13	48-53 y	Bachelor	Medium	€100.001 - €120.000
Yes	13	4.04	4.08	4.00	4.15	3.92	7	6	48-53 y	Bachelor	Medium	€100.001 - €120.000
No	15	2.68	2.73	3.07	2.60	2.33	8	7	48-53 y	Master	Low	€80.001 - €100.000
Human	30	3.36	3.57	3.17	3.40	3.30	16	14	42-47 y	Master	Medium	€100.001 - €120.000
Yes	15	3.56	3.80	3.27	3.67	3.53	9	6	36-41 y	Master	Medium	€100.001 - €120.000
No	15	3.15	3.33	3.07	3.13	3.07	7	8	48-53 y	Master	Medium	€100.001 - €120.000
Profile 4	**7**	**3.39**	**3.57**	**3.43**	**3.29**	**3.29**	**3**	**4**	42-47 y	Bachelor	Low	€80.001 - €100.000
Robo	4	2.81	3.00	3.00	2.50	2.75	2	2	42-47 y	Master	Medium	€100.001 - €120.000
Yes	1	3.25	4.00	3.00	3.00	3.00	1	0	30-35 y	Master	Medium	€100.001 - €120.000
No	3	2.67	2.67	3.00	2.33	2.67	1	2	42-47 y	Bachelor	Medium	€80.001 - €100.000
Human	3	4.17	4.33	4.00	4.33	4.00	1	2	48-53 y	Bachelor	Low	€60.001 - €80.000
Yes	2	4.13	4.00	4.00	4.50	4.00	1	1	48-53 y	Bachelor	Low	€60.001 - €80.000
No	1	4.25	5.00	4.00	4.00	4.00	0	1	48-53 y	Master	Low	Prefer not to say.
Profile 5	**34**	**2.96**	**2.97**	**2.94**	**2.82**	**3.12**	**18**	**16**	36-41 y	Master	Medium	€100.001 - €120.000

Robo	16	2.92	3.06	3.13	2.63	2.88	10	6	36-41 y	Master	Medium	€100.001 - €120.000
Yes	4	3.06	3.25	3.25	3.25	2.50	2	2	36-41 y	Master	Medium	€100.001 - €120.000
No	12	2.88	3.00	3.08	2.42	3.00	8	4	36-41 y	Master	Medium	€80.001 - €100.000
Human	18	3.00	2.89	2.78	3.00	3.33	8	10	42-47 y	Master	Medium	€100.001 - €120.000
Yes	4	3.81	3.00	3.75	4.00	4.00	0	4	42-47 y	Master	Medium	€100.001 - €120.000
No	14	2.77	2.86	2.50	2.64	3.07	8	6	42-47 y	Bachelor	Medium	€100.001 - €120.000
Total	*191*	*3.33*	*3.39*	*3.27*	*3.31*	*3.33*	*94*	*97*				

Table 3 – Logit Model.

The Logit Regression was performed in STATA using a sample of 166 observations. In addition to the observation that was excluded in the OLS model, countries with 2 or fewer observations were also dropped from the Logit regression analysis. This decision was made due to the limited sample size, which was deemed inadequate for accurately assessing any effects in these specific countries.

Similarly, to the OLS model, Global Average Trust, Profile, Education, and constant are significant and present the same direction in both models. Group and the interaction term remain not significant.

Log Likelihood: -82.69336 Pseudo R^2: 0.2786

Logit Regression - Dependent Variable: Follow/Not Follow Financial Advice					
Variable	Coefficient	t- statistics	P-Value	Confidence	Interval
Treatment	-0,3412 (2,0856)	-0,1600	0,8700	-4,4289	3,7465
Global Average Trust	-1,6122*** (0,4585)	-3,5200	0,0000	-2,5108	-0,7136
Treatment##Global Average Trust	-0,0678 (0,6040)	-0,1100	0,9110	-1,2517	1,1161
Profile	0,4997*** (0,1510)	3,3100	0,0010	0,2037	0,7958
Age	0,1004 (0,0861)	1,1700	0,2430	-0,0683	0,2692
Female	0,1652 (0,4486)	0,3700	0,7130	-0,7142	1,0445
Education	-1,0217** (0,3750)	-2,7200	0,0060	-1,7567	-0,2866
Financial Education	-0,1445 (0,2611)	-0,5500	0,5800	-0,6562	0,3672
Income	0,0020 (0,0776)	0,0300	0,9800	-0,1501	0,1541
Country (Brazil as reference)					
Netherlands	0,0997 (0,5825)	0,1700	0,8640	-1,0419	1,2413
USA	-1,0880 (1,5460)	-0,7000	0,4820	-4,1181	1,9422
Constant	7,7601*** (2,1750)	3,5700	0,0000	3,4971	1,2023

Table 4 – Qualitative Analysis – Comments section

	Robo-Advisor (21)	Human Advisor (27)	*Total (48)*
Nature of Comment			
Trust	2	4	*6*
Conflict of interests	0	6	*6*
Advice	7	14	*21*
Suitability	5	3	*8*
Robo	7	0	*7*
Global Average Trust	2,4	3,02	*3*
Average T1	2,48	3,11	*2,83*
Average T2	2,81	2,93	*2,88*
Average T3	2	2,96	*2,54*
Average T4	2,33	3,07	*2,75*
Characteristics			
Average Profile	3,24	3,48	*3,38*
Male	11	12	*23*
Female	10	15	*25*
Average Age	36-41	36-41	*36-41*
Average Education Level	Bachelor/Master	Bachelor/Master	*Bachelor/Master*
Average Financial Education Level	Medium	Medium	*Medium*
Average Income per year	€80.001 - €100.000	€80.001 - €100.000	*€80.001 - €100.000*
Country			
Brazil	19	20	*39*
Netherlands	2	6	*8*
Denmark	0	1	*1*
Mexico	0	1	*1*